

8-2013

# UNDERSTANDING THE ANTECEDENT COMPETENCIES OF ORGANIZATIONAL RISK MANAGEMENT CAPABILITIES

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UNDERSTANDING THE ANTECEDENT COMPETENCIES OF  
ORGANIZATIONAL RISK MANAGEMENT CAPABILITIES

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A Dissertation  
Presented to  
the Graduate School of  
Clemson University

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In Partial Fulfillment of the  
Requirements for the Degree  
Doctor of Philosophy  
Management

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by  
Jason Matthew Riley  
August 2013

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## **ABSTRACT**

Hurricanes, tsunamis, and terrorism, are visible catastrophes that disrupt continuity for many organizations. Yet behind the curtain, there are multitudes of smaller events that cause supply chain disruptions. For example, quality issues, shipping delays, information system malfunction, demand spikes, and inventory mismanagement can quickly ripple from one supply chain to another. Practitioners work feverishly to contain small interruptions, while large disruptions can upset the supply chain for multiple organizations and depress an organization's financial valuation by up to 40%.

This study extends risk management thinking by exploring behavioral-based practices, rather than buffer inventory, redundant capacity, or financial countermeasures, as these behavioral tactics affect employees and emanate from the culture of the organization. We specifically, research competencies that improve an organization's structure and orientation. Internal integration, information sharing, and training reflect antecedent competencies that provide structure and encourage internal connectedness. Common vision, supply chain disruption orientation, organizational learning, and routine rigidity represent competencies that influence the organization's orientation, a proxy for culture. Previous operations research has investigated these antecedents, but rarely have they viewed them from a risk management perspective.

We also determine how organizations use risk management capabilities to understand supply chain disruption. To do this, we develop a conceptual disruption management framework that seeks to align the probability of disruption and the

predictability of consequences with an organization's supply chain strategy. The model should help practitioners select an appropriate supply chain strategy from among several alternatives. The output is a risk management strategy grounded in supply chain flexibility, risk and loss mitigation, agility, or resilience.

We also operationalize two new risk management measures: warning and recovery capability. Warning capability refers to an organization's ability to scan for and communicate information about potential and actual supply chain threats. When properly developed, this capability should enable organizations to better identify supply chain threats. Recovery capability represents an organization's pre-emptive and reactive response capacity. Developing these capabilities allows practitioners to effectively position and utilize resources to speed up supply chain recovery.

The evidence indicates that organizations can develop behavioral-based competencies and capabilities as a method to better anticipate and combat supply chain risk. When studying orientations that influence the culture of an organization, we found that managers should develop their common vision, supply chain disruption orientation, and organizational learning competencies as a way to address supply chain risk. The evidence tells us that each competency positively influences the organization's risk management capabilities and overall performance. Additionally, the data implies that organizations must manage their routine rigidity and information quality levels; otherwise, they may experience a degradation of their risk management capabilities. Structurally, we found that internal integration and training affect an organization's warning and recovery capabilities and leads to improved performance. While recovery

capability directly improves performance, we find that an organization's warning abilities affect performance only when recovery serves as an intermediary. The benefit of this approach is that managers develop the employees and the organization itself, rather than investing in resources that may never be used.

## DEDICATION

Dr. Janis Miller offers time, a most valuable resource. Hour upon hour, we teased out ideas and language. She provided an excellent atmosphere for doing research. I find her influence within every draft and thought. For this, I say 谢谢.

Dr. V Sridharan encouraged me to think about my research and writing, yet offered support as I worked towards my goals. In turn, I say thank you.

Dr. Rich Klein helped me simplify my thinking. Without his guidance, I would have had an unruly dissertation. Thank you for the help.

DeWayne Moore has been a calming and thoughtful influence. He made statistics understandable and usable. For him, I offer a quote: There are lies, dam lies and statistics.

My thanks also goes out to my fellow doctoral students. In particular, I send gratitude to Sriram Venkataraman, Kevin Craig, and Tracy Johnson-Hall. Each calmed, chided, and encouraged me through this process.

My father, Terry Riley offered a sounding board, advice, and direction during many conversations. Dad, a simple thank you is not enough.

My daughters, Danielle, and Elise, I profusely thank them for their love and support. Danielle encouraged me with her spirit for adventure and learning. She makes my world splendid by being monumental. Every day she jumps at the world making it better with her enthusiasm. Keep it up. Elise offers love, truth, and a simple cuddle. She aced her first statistics final with a 103-degree fever, but always kept smile. Please keep being majestic. I love you both.

Debbie, the love of my life. Besides endless encouragement, she made me better, helped me see the world, offered a shoulder to lean on, and loved me without question. She simply makes my world a better place. You are my best friend, my one and only, you're my everything. I love you.

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## **EXECUTIVE SUMMARY**

### **Introduction**

Hurricanes, tsunamis, and terrorism, are visible catastrophes that disrupt continuity for many organizations. Yet behind the curtain, there are multitudes of smaller events that cause supply chain (SC) disruptions. For example, quality issues, shipping delays, information system malfunction, demand spikes, and inventory mismanagement can quickly ripple destructively from one supply chain to another. Practitioners work feverishly to contain small interruptions, while large disruptions can upset the SC for multiple organizations and depress an organization's financial valuation by up to 40% (Hendricks and Singhal, 2005). Organizations need to develop less resource intensive tactics to manage and mitigate supply chain risk.

To address SC risk, organizations develop strategies to lower the probability of occurrence, reduce the impact of disruption, and improve recovery times so a SC can quickly return to a steady state. While risk management requires comprehensive strategies, we find most academic research addresses SC risk with redundant inventory and/or capacity. If overdone, these mitigation techniques are costly and force organizations to idle valuable resources, which they will not effectively turn until the next SC disruption.

This study extends risk management thinking by exploring behavior-based practices, rather than buffer inventory, redundant capacity, or financial countermeasures. Behavior tactics affect employees and emanate from the culture of the organization

(Zsidisin, 2003; Simchi-Levi, Kaminsky, and Simchi-Levi, 2010). This research follows the advice of experts who suggest that risk management tactics be embedded in day-to-day activities as part of the organization's culture (Simchi-Levi, 2010). Albeit, few researchers have empirically tested these behavior-based strategies within current literature.(Sohdi, Son & Tang, 2012). Ellis, Henry, and Shockley (2010) focused on the magnitude and the probability of supply disruption within the automotive industry and Tucker (2004) categorizes the dimensions of failure within the nursing environment. While informative, neither research investigates capabilities and competencies simultaneously. To fill this gap, we operationalize two risk management capabilities, warning and recovery, and test empirically the antecedent competencies that enhance organizational risk management capabilities.

In this research, we investigate whether organizations can develop behavior-based competencies and capabilities to reduce SC risk and the resulting disruption consequences. We specifically research competencies that improve an organization's structure and orientation. Structural competencies include internal integration, information sharing, and training. These structural antecedents encourage internal connectedness. Orientation competencies encompass a common vision, SC disruption orientation, organizational learning, and routine rigidity. These antecedents influence the organization's orientation, a proxy for culture.

We also determine how organizations use risk management capabilities to understand SC disruption. To do this, we operationalize the warning and recovery



capability measures proposed, but never tested, by Craighead et al. (2007). Warning capability refers to an organization's ability to scan for and communicate information about potential and actual SC threats (Craighead et al., 2007). When effectively developed, this capability should enable organizations to better identify potential and actual SC threats. Recovery capability represents an organization's pre-emptive and reactive response capacity (Craighead et al. 2007). Developing these capabilities allows practitioners to effectively position and utilize resources to speed up SC recovery.

By developing measures for warning and recovery capabilities and then investigating how they relate to antecedent competencies and organizational performance, we provide practitioners a new way to think about and manage SC risk. Rather than buffering with costly resources, we advocate behavior-based risk management tactics. These practices enhance the organization and the practitioners running the processes, save money, and broaden the tactics used to manage supply chain risk.

### **Approach**

Using three essays, this research investigates (1) how to align the SC and risk management strategies, (2) measure an organization's warning and recovery capabilities, and (3) develop antecedent competencies to mitigate SC disruption. This offers a practical approach for managing SC risk, which helps reduce costs and improve the interconnectedness and culture within an organization.

The first essay develops a conceptual disruption management framework that seeks to align the probability of disruption and the predictability of consequences with an organization's SC strategy. We believe disruption consequences are an important component of SC disruption that has been overlooked by previous research. Most risk management models focus on risk sources or the cause of a disruption as part of their strategy (e.g. Norrman and Jansson, Kleindorfer and Saad', Knemeyer et al.'s'). Since disruptions, with a common cause, can manifest in many different ways, this approach lacks depth. Alternatively, by focusing on disruption consequences, managers can address many SC threats more effectively. Specifically, our model helps practitioners select an appropriate SC strategy from four quadrants (Figure 1). The output is a risk management strategy grounded in SC flexibility, risk and loss mitigation, agility, or resilience. We also incorporate warning and recovery capabilities into the framework and discuss how an organization can leverage these capabilities to improve its overall risk management process.

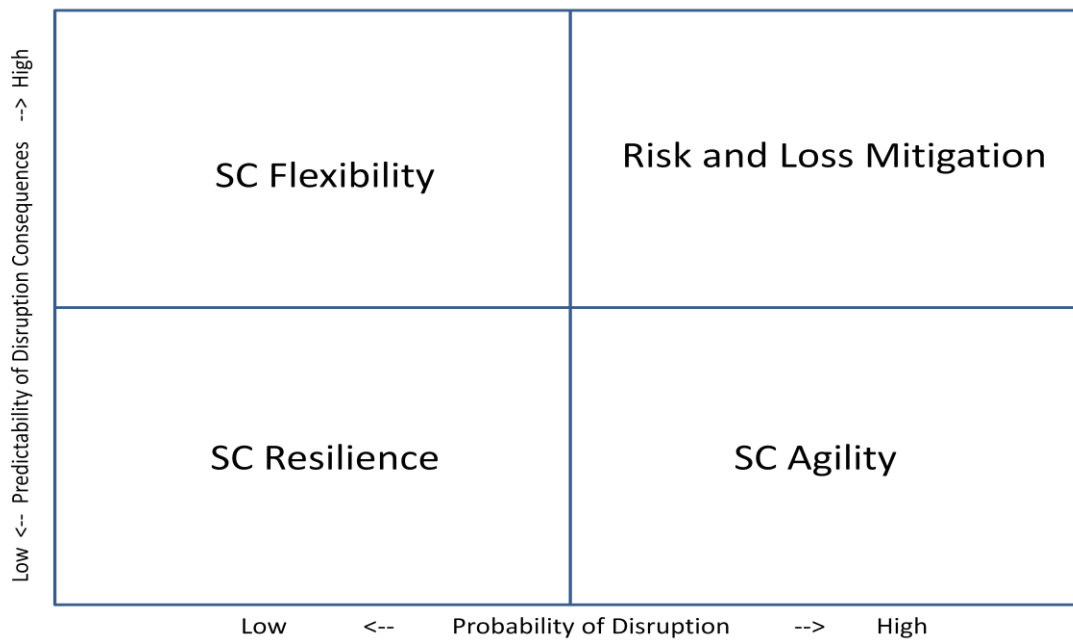


Figure 1: Disruption management framework

The second essay develops psychometrically valid measures for risk warning and disruption recovery capabilities. Craighead et al. defined these capabilities in 2007; however, no one has developed measures or a measuring instrument, as of today. Following Noar's (2003) validation procedures, which provides a roadmap from literature review to validity testing, we developed new valid and reliable measures. Evidence from this study will help practitioners understand the relationships between four organizational orientations (common vision, SC disruption orientation, organizational learning, routine rigidity), the proposed capabilities (warning and recovery), and performance. (See Figure 2)

In addition, we also test the effect of a mediating variable, information quality on competency-capabilities relationships. This includes the direct linkage between common vision and the warning capabilities construct (1A), the direct effect between common vision and recovery (1B), and the indirect relationship of common vision and recovery, which is mediated by warning capabilities (1C). Additionally, hypothesis 1D, 2C, 2D, 3C, and 3D test the moderating effect of information quality on the relationships between the four competencies and the two risk management constructs. Practitioners can use the new measurement tool to benchmark their own risk management capabilities and assess the preparedness of their organization to counter a SC disruption.

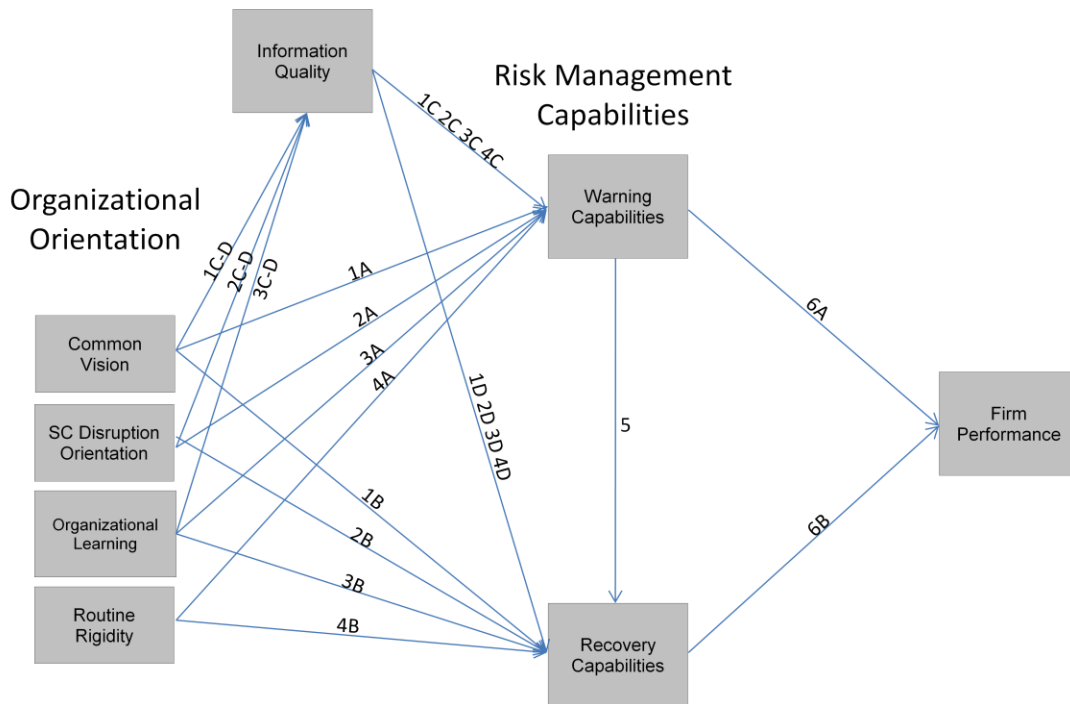


Figure 2: Proposed model for dissertation essay 2

The third essay investigates the effectiveness of structural competencies as a method to improve internal connectedness and communication. Similar to essay 2, we leverage Craighead et al's definition of warning and recovery capability and test a new model with the newly validated measures. Specifically, we develop and test a model that examines the relationships between the three organizational competencies ( internal integration, information sharing, and training), two risk management capabilities (warning and recovery), and performance (Figure 3). The model is tested using data from the healthcare industry. The healthcare industry provides an excellent research venue, as most organizations are actively seeking ways to improve service and cut costs, especially given that 40% of a hospital's budget is dedicated to SC expenditures (Sweet, Hamilton, and Willis, 2005). We also investigate a moderating relationship, which represents an interaction between training and organizational size. Licensed beds (BEDS) is a proxy for organization size. Hospital managers and SC professionals should use the new measures to enhance their connectedness and improve the organization's disruption management capabilities.

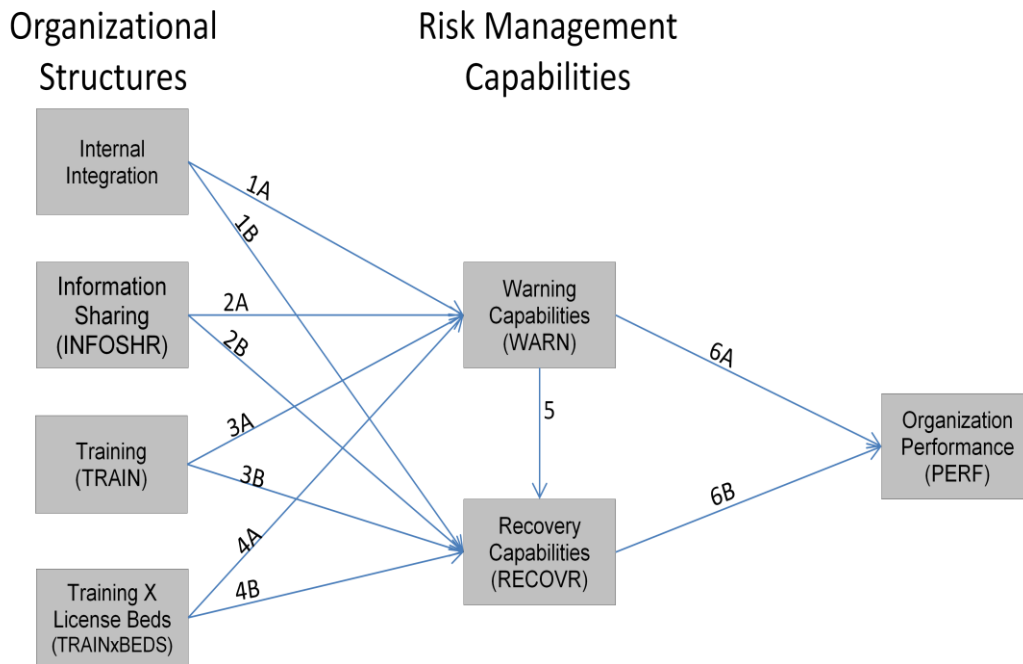


Figure 3: Proposed model for dissertation essay 3

In all three essays, we leverage high reliability theory (HRT) as it describes how organizations can design and develop highly reliable supply chains to stave off accidents and the consequences of disruption (Rochlin, LaPorte, & Roberts, 1987; Weick & Roberts, 1993). Unlike other operations management theories, HRT encourages organizations to value simultaneously both safety and profitability. By studying SC risk and SC management with this lens, we illustrate how organizations can improve their internal competencies and organizational risk management capabilities by learning from environmental cues and then transforming the that knowledge and existing resources into new capabilities.

Each essay fills a gap within the existing SC and risk management literature. Our disruption management framework ( essay 1), provides a new perspective concerning the mitigation of SC disruption. Existing models focus on the sources of risk or seek to differentiate between the causes of disruptions. In 2012, Sohdi, Son, and Tang asked researchers to clarify and seek consensus around the SC risk management definition. By studying disruption consequences, rather than just the cause alone, we add depth to and help clarify the SC risk management definition. In addition, Manuj and Mentzer (2008) stated that there was limited research into risk management moderators. By conducting research on the moderating and mediating affects within the risk management paradigm, we fill an existing gap.

Lastly, the second and third essays investigate mediating and moderating effects. the second and third essays provide empirical evidence about behavior-based risk management techniques within organizations. Sohdi, Son, and Tang (2012) argue that there is a dearth of empirical SCRM research within OM literature. Our research, therefore, is designed to provide empirical evidence concerning the linkages between the antecedent competencies, newly operationalized risk management capabilities, and performance. This evidence should assist managers as they develop a more comprehensive SC risk management strategies. Besides inventory and/or capacity, we envision that organizations will enhance connectivity and develop the organization's culture as a means to combat SC risk.

## **Methodology**

To understand the effectiveness of the proposed behavior-based risk management practices, we employ both exploratory and confirmatory techniques. This allows us to triangulate our findings and improve their nomological validity. Initially, we examine existing SC risk and risk management literature. This provides a foundation from which we build the disruption management framework and the two structural models used within essay 2 and 3. We also explored complementary topics including crisis management, SC resiliency, SC agility, and disruption management. Each topic provides insight on how to combat threats and recover once a disruption occurs.

We then used an item-to-construct sorting procedures (Q-sort) and asked respondents to link survey questions to latent construct definitions (Menor and Roth, 2007, p 831). During the Q-sort process, respondents also identified incomplete definitions and misleading concepts. This process allowed us to establish construct and face validity for the proposed models and the two survey instruments (Anastasi, 1988). We developed questions and definitions, for each competency, capability, moderator, mediator and performance construct.

To corroborate construct measures, the primary author then conducted interviews with SC and risk management professionals. The interview protocol was discovery oriented and focused on the appropriateness of the proposed model, construct definitions, and survey questions. We also asked interviewees to review the survey instrument. The primary investigator directed these interviews and asked clarifying questions. We



recorded the interviews and made changes to the final survey instrument based on the experts' input.

For the confirmatory phase, we collected pilot, pretest, and two full data sets, as suggested by Noar (2003). The primary investigator collected pilot data from professional MBA students (evening program) and pretest data from procurement directors associated with university hospitals. We then collected the final data set for essay #2 from procurement professionals across industries. Data for essay #3 was collected from material managers within US hospitals. Multiple data collections from several demographics improves both the validity and reliability of the survey measures.

We then used confirmatory factor analysis (CFA) to assess the scale's unidimensionality, construct reliability, and criterion validity. While most data characteristics were within acceptable parameters, we found that data for essay #2 exhibited common method bias. This occurred because we collected only one respondent per organization. Once identified, we controlled for this bias in subsequent analysis using a method factor. We also found that the warning and recovery capabilities constructs within essay #2 did not exhibit discriminant validity. Thus, we amended the conceptual model to reflect a single multidimensional construct called disruption sensing and response capability (See Figure 4). The new construct reflects four risk management dimensions: scanning, communication, proactive response, and reactive recovery.

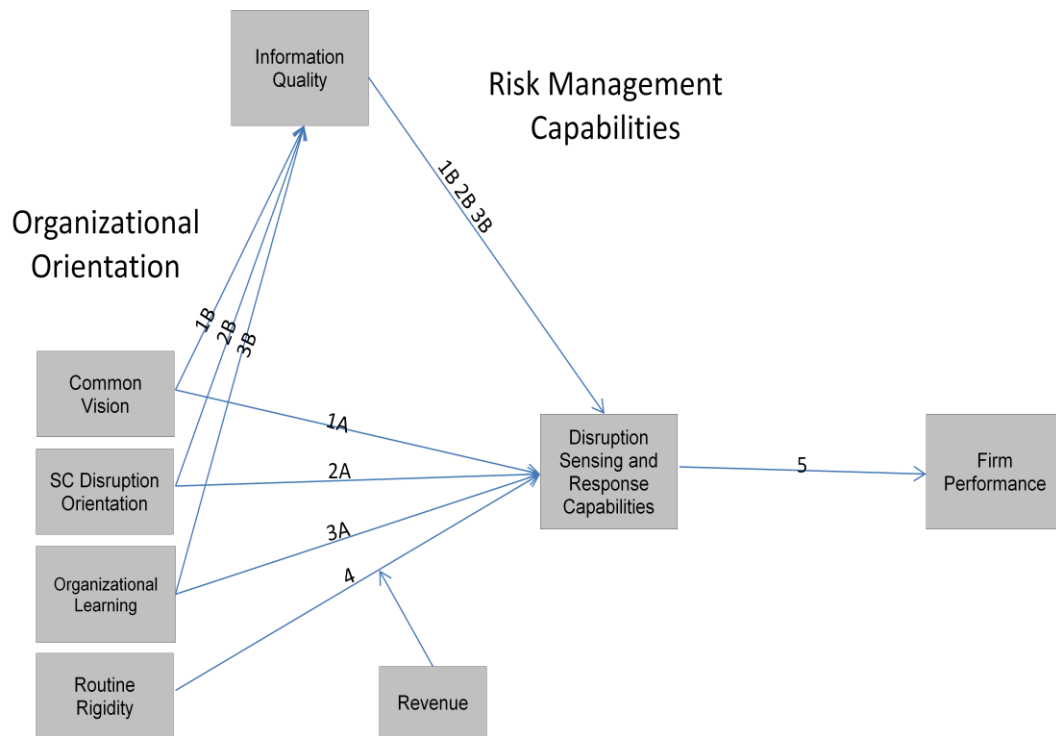


Figure 4: Amended model for essay 2

### **Managerial Implications**

As supply chains expand and become more complex, organizations must realize that the probability of disruptions also increases. To offset an inevitable disruption, managers must develop risk management tactics that lower occurrence probabilities, reduce potential impact, and/or shorten recovery times so a SC can return to a state of normalcy. In this study, we suggest that behavior-based risk management techniques enable managers to embed risk management competencies and capabilities into the organization's culture.

This research helps practitioners in three ways: first, by developing new measures for warning and recovery capabilities, organizations have a method to quantitatively measure and benchmark their SC risk management capabilities. Second, by investigating the antecedent competencies of the warning and recovery capabilities, we help practitioners understand how behavior-based competencies can bolster an organization's risk management capabilities. Specifically, we provide guidance as managers develop both organizational orientations and internal connectedness structures. Third, by teasing out the effects of information quality and organization size, we illustrate the importance of moderators and mediators on competency and capability development. From this research, we anticipate that managers will include behavior-based competencies and capabilities in their arsenal of SC risk management tools.

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# **INCORPORATING THE PREDICTABILITY OF CONSEQUENCES INTO A DISRUPTION MANAGEMENT FRAMEWORK**

## **Abstract**

We introduce a disruption management framework that incorporates both the probability of disruption and predictability of the resulting consequences. The resulting model prescribes one of four supply chain strategies: flexibility, risk and loss mitigation, agility, and resilience. We also discuss how organizations can exploit warning and recovery capabilities to improve the selected supply chain strategy. Managers can leverage our framework within a comprehensive risk management process to develop tactics aligned with risk management, supply chain, and overall operating strategies to overcome a range of disruption consequences.

## **Introduction**

Researchers recommend developing a risk management strategy that includes the consequences associated with supply chain disruption (Greenberg & Cramer, 1991). Yet, existing models focus primarily on the sources of supply chain (SC) threats. Managers generally identify the source of a risk in the early stages of the risk management (RM) process, which allows them to categorize threats for further assessment. This approach fails to incorporate the consequences of disruption into either the assessment and mitigation processes or even the broader organizational RM strategy. Hence, practitioners should consider not only the source of a disruption, but also the resulting consequences when evaluating SC risk.

When evaluating SC disruptions based on the predictability of the consequences, practitioners are better able to select appropriate mitigation tactics. For instance, the Chinese New Year holiday is a predictable SC disruption, which shuts down production facilities for a specified period. Managers confidently select countermeasures, as they know how and when the consequences will manifest. i.e. the organization can reasonably estimate inventory shortages. Early shipments and temporary inventory buffers are logical and financially prudent. This strategy is preferred, as it will generally cost less to fund preventative countermeasures, rather than responding to the disruption afterwards.

On the other hand, a hurricane (risk source) is unpredictable because it is difficult to articulate when a storm will appear or where it will actually make landfall. Further, a hurricane can manifest into a Katrina-type disaster (category 4), or alternatively a

category-one storm, with little aftereffect. Experts need to understand wind intensity, expected rainfall, and the inland storm surge, before assessing these risk sources. Yet, consequences of different grades of hurricanes can be better calculated. i.e. insurance companies are able to predict the probability of loss for various hurricane types.

There are also situations where consequences overlap or stem from multiple sources of risk. For example, a machine may shut down due to a shortage of raw materials, a break in the electrical current, or a component within the machine actually failing. In this case, vendor failure, an electrical outage, and component breakage are the sources of a risk, while the machine shutting down is the actual consequence. The consequence is predictable, because practitioners can determine the time between failures and the time associated with repair (e.g. mean-time-to-failure (MTTF) and mean-time-to-repair (MTTR)). With this knowledge, managers are able to identify countermeasures, such as inventory or redundant capacity, which keeps the production line up and running. This also streamlines the RM process, because one safeguard, rather than three, can mitigate the consequence of a disruption.

Existing RM frameworks emphasize risk identification, probability assessment, countermeasure evaluation, and countermeasure deployment (Knemeyer, Zinn & Eroglu. 2009). Researchers design these models to balance the probable losses of an identified threat with the financial costs of countermeasures. To compute potential losses, assessment algorithms multiply the probability of disruption by the loss estimates of a corresponding SC disruption. With this equation, the annual losses associated with

frequent minor disruptions can theoretically equal the losses of a low probability/infrequent disruption with severe consequences.

Our framework accounts for the predictability of consequences, so practitioners can better understand the manifestations of a SC threat. We propose a disruption management framework that evaluates the probability of disruption and the predictability of consequences, to prescribe a SC strategy that fits best with the risk characteristics of disruption threats faced. We also incorporate warning and recovery capabilities into the framework and discuss how to leverage these capabilities to improve an organization's comprehensive RM process. When taken together, practitioners can use our framework to align the organization's SC, RM, and overall operating strategies.

After reviewing existing supply chain risk management (SCRM) frameworks, we find three gaps worth investigating. To address these deficiencies, this article proceeds in the following manner. First, we review the dimensions of existing SCRM frameworks. We appraise the seminal RM frameworks to understand their contributions and limitation. This includes defining and assessing the four key terms relevant to most RM models: *risk identification*, *assessment*, *mitigation*, and *responsiveness*. Second, we introduce our own disruption management framework, which includes both the probability of disruption and the predictability of consequences. We discuss four SC strategies: *supply chain flexibility*, *risk and loss mitigation*, *agility*, and *resilience*. We illustrate the utility and advantages of our framework through representative examples. Third, we discuss how warning and recovery capabilities support the SC strategies derived from our model. This includes a



discussion on how our framework addresses the gaps identified within the SC and RM literature. After reviewing the appropriate gaps, we predict how managers may use our model to mitigate SC risk, whereby consequence assessment versus risk cause assessment, can help organizations save money, reduce inventory levels, as well as induce better preparation for SC disruptions.

### **Key Contributions of Existing Supply Chain Risk Management Frameworks**

When reviewing current SC risk and business continuity planning (BCP) frameworks, we find five key contributions to be particularly informative. Together, these models delineate areas important to models of risk preparation, impact reduction, developing SC partners, BCP, and response best practices. We illustrate the contribution of each model, as well as highlight how each alone might leave a gap because they focus on the sources of SC risk rather than disruption consequences. Accordingly, we provide our model, predicated on the latter later in this paper.

To start, Norrman and Jansson (2004) offer a framework that advocates a proactive RM process. This suggests that organizations develop a RM process before the actual disruption occurs. In their research, Ericson, a Swedish telecom company, develops a multi-step process that combines risk identification, assessment, treatment, monitoring, incident handling, and contingency planning. Utilizing this framework, Ericsson has been able to improve communications with its supply base during both preparation and post incident stages. While, we embrace the proactive nature of this

model, it focuses on the cause or sources of risk (Norrman and Jansson, 2004, p 438). By adding a step that proactively assesses disruption consequences, managers can develop specialized RM tactics. We expect both mitigation and response activities to be different for a category 1 versus a category 5 hurricane.

Next, Kleindorfer and Saad (2005), in one of the most cited RM models, describe two risk categories: risks associated with the uncertainty of supply and demand coordination and risks linked to events such as terrorism and natural disasters. Within this model, they propose that organizations engage in a two-front battle when managing SC risk. First, managers should work to reduce the frequency and severity of all types of SC risk. Second, both the organization and its SC partners need to improve their capacity to handle uncertainty. This represents a call to arms, which demands that organizations focus on the entire SC, not just their own facilities. However, the first step of their SAM model (S)pecifies that manager should seek out risk sources and vulnerabilities by thinking about operational contingencies, natural hazards, and events such as political instability and terrorism (p 54).

By incorporating, a process to identify how consequences manifest themselves, we argue that managers could improve the SAM model. For example, Kleindorfer and Saad use the August 14, 2003 grid blackout as an example of an equipment failure. We believe that an organization, along with its SC partners, would prepare for a large-scale blackout, like the August 14 event, much differently that they would a small transistor that knocks out the electricity for a single building. The only way to (A)ssess and

(M)itigate (the last two steps of the SAM process) these differences is to discuss different disruption manifestations. We put forth, that managers can improve the overall SAM process by assessing the consequences associated with a SC disruption.

Third, Handfield, Blackhurst, Rungtusanatham, and Craighead (2008) compare executive responses to benchmark risk and mitigation practices. By studying the actions taken during actual disruptions, the authors identify best practices to manage and mitigate threats. Their key takeaway is that organizations may have to redesign the SC or pursue external partnerships to overcome certain risks.

While the Handfield's framework focuses on discovering pinch points where a SC disruption could occur, it does not call out either the source or the consequences of a SC disruption. Specifically, the article urges managers to screen for vulnerabilities and then quantify an organization's level of SC risk. What is interesting is that within the formula for SC risk are parameters for revenue loss and the cost to stabilize the SC disruption. We assert that managers will need to understand the consequences associated with a SC disruption in order to generate these estimates. For example, the revenue loss estimates for a category 5 hurricane should be significantly higher than for a category 1 storm. By including a step to screen for disruption consequences, managers should be better informed when attempting to quantify the level of risk for a specific SC node.

Fourth, the Knemeyer et al. (2009) catastrophic risk framework encourages organizations to manage disruption even when they have low occurrence probabilities. Their work offers insight into implementation issues and suggests five alternative

approaches to countermeasure selection (1) assume the risk, (2) purchase insurance to offset the potential losses, (3) dependency reduction, (4) invest in a location to minimize the consequence of disruption, or (5) relocation of targeted facilities. This framework contributes to our understanding of RM by considering low probability threats.

Within this process, Knemeyer and colleagues argue that managers need to initially identify the location of potential threats” (p 147) and then estimate the probability and dollar loss associated with a location-disruption combination. Managers should discuss potential disruption consequences during the identification process to improve their estimation process. This can be achieved by working through possible consequence scenarios early in the assessment process.

Finally, Zsidisin, Melnyk, and Ragatz (2005) offer a framework to help practitioners develop business continuity plans (BCP) as a mechanism to manage catastrophic risks. The authors draw from case studies and build a BCP framework by thinking about low probability and difficult to predict events. Key to this article is that practitioners should create awareness towards risk and threat prevention within the organization. Stated differently, managers can develop organizational countermeasures, competencies and capabilities, to mitigate catastrophic supply risks.

## **Dimensions of a Supply Chain Risk Management Framework**

While the above models use a number of different categories in their RM models, there are essentially four common elements within existing RM frameworks: risk identification, assessment, mitigation, and responsiveness (Sodhi, Son, and Tang, 2012). In their conclusion, Sodhi and colleagues suggest that organizations should incorporate these steps into any comprehensive RM process. Accordingly, we provide a more detailed review of each term as it is typically defined and applied by SC practitioners, and the possible limitations of such applications. Whereby, in contrast, a model predicated on disruption consequences, our model, might fill the gap the standard risk-source predicated model leaves.

### *Risk Identification*

During the initial step within most RM processes, the management team identifies a list of threats or sources of risk, which they believe threaten the supply chain, i.e., *risk identification*. This includes risks such as machine breakdowns, vendor failures, labor strikes, fires, hurricanes, and terrorist attacks. Practitioners should use the risk identification step to identify potential threats to their organization and extended SC. In order to improve the identification process, risk-mapping methods such as event tree analysis and fault tree analysis are available (Norrman & Jansson, 2004). However, generally speaking, identifying risks is difficult, and therefore, managers avoid making decisions about risky events when possible. Bounded rationality describes how humans

employ simple models to make decisions when unclear or unfamiliar information is present. This is the case, since the managers involved throughout the identification process tend not identify risks proactively, logically they may also not foresee or comprehend the consequence associated with a SC disruption.

We envision the risk identification step alternatively. To populate our disruption management framework, team members, should identify both the source of and the consequences associated with a SC disruption. For example, the management team may identify a logistic provider's labor issues (possible Fed Ex strike) as a potential threat. In this case, the source of the disruption is the labor issue, while the resulting consequence is the lack of overnight transportation services. By including information about the resulting consequences, managers can utilize our disruption management framework and select an appropriate SC strategy that complements the resulting mitigation tactics. We believe this qualitative process benefits from brainstorming sessions and SC disruption experience. The outcome of this initial step is list of risk sources and consequences that the RM team believes can threaten the organization's SC. With a broad list of SC threats and potential consequences, practitioners have the information necessary when working through the balance of the RM process.

### *Assessment*

Traditionally, the next step in RM includes *assessment*, whereby managers analyze information about threats identified in the first portion of the RM process and

create a priority ranking based on their understanding of the probabilities and disruption likelihood. Regardless of how robust an assessment process is, organizations typically attend to only the low-impact, recurrent risks and ignore catastrophic events with low probabilities (Chopra & Sodhi, 2004). This occurs, because the individuals participating in the assessment process struggle to envision or understand the probabilities associated with ambiguous risks. Stated differently, managers are reluctant to utilize objective data such as probability estimates to evaluate infrequent risks. In addition, there is also evidence that the RM process itself may push managers towards a conservative tack. Barth (2010), for example, identifies several barriers to risk assessment, including a lack of resources and the management's reluctance to invest in events that may never materialize. Further, when analyzing the statistical probabilities associated with a disruption event, most practitioners have been trained (in a good number of basic statistics and Master of Business Administration (MBA) classes) to remove outliers from the analysis.

To overcome the conservative bias, some organizations use a catastrophic risk management matrix (Figure 1) to assess the probability of a disruption event (Knemeyer et al., 2009). Frameworks such as these are important because not considering catastrophic risk creates a host of issues within the assessment process. Consider for example 100-year floods. Generally, managers will exclude these outliers from a comprehensive flood-plain analysis and bias the probability estimates.

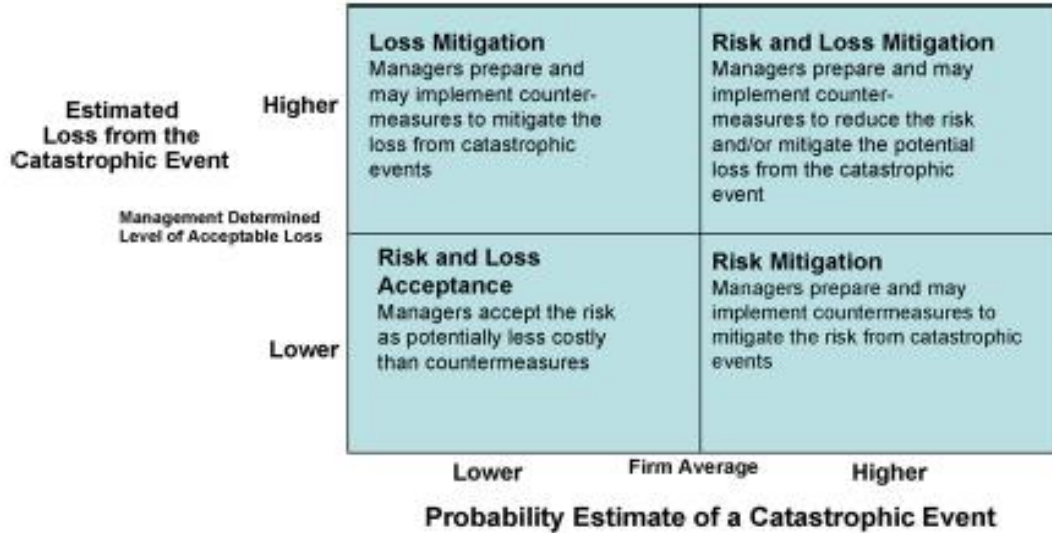


Figure 1: Catastrophic Risk Management Matrix – Adopted from Knemeyer, Zinn, & Eroglu, 2009

We recommend a revision of the *assessment* step that introduces a more calculable predication of disruption consequences. We argue that such a model is more effective in preparing organizations for all types of risks, but also eliminates the more difficult mathematics of risk probability (consequence size assessment is simply easier as it is more predicatble), and in turn, risk assessment improves, saving the organization money overall. Using our framework, practitioners evaluate the consequences associated with a SC disruption scenario and then create a priority list. Practitioners should exploit the assessment process to evaluate how an identified risk will affect an organization and the extended SC (Zsidisin, Ellram, Carter, & Cavinato, 2004). Initially, information feeds a quantitative analysis process and provides probability estimates on the frequency and



impact of various disruptions. Only then can topic experts superimpose qualitative information into the analysis process to improve understanding.

Managers assess the predictability of the resulting consequences along with the probability of occurrence. With these dimensions, the assessment team can draw different conclusions than they would with a traditional framework that focuses on the cause of a SC disruption. For example, a traditional analysis will consider a financially unstable vendor to be a significant source of risk. In addition, if the vendor happens to be a large, by either volume or dollar spend, the analysis team will assign a large impact/vulnerability factor and further increase the threat priority. However, with our framework, the assessment team teases out the predictability of the consequences and can theoretically draw different conclusions. Using the example of a financially unstable vendor, the consequence associated with the threat is the shortage of specific raw materials, not the vendor's financial instability. It is predictable, because the focal organization can specify the items and quantity needed. With this new information, managers are able to reduce the level of uncertainty and the priority ranking associated with a specific SC consequence. In addition, information about the resulting consequences should make future decisions about countermeasures and mitigation tactics easier to comprehend. Specifically, a backup supplier could be qualified. By identifying the consequences associated with a SC threat rather than just a broad risk cause, practitioners should be better able to understand SC risk. This occurs as practitioners think about previous SC experiences and develop a SC disruption orientation.

## *Mitigation*

The third step common to existing RM processes is the *mitigation* procedure, which practitioners employ to evaluate the functionality and cost associated with risk reducing or recovery efforts, including countermeasure evaluation and selection. For example, when the RM team has prioritized quality issues of a specific supplier, it has a number of options to address the risk source.

1. The focal organization can incentivize the supplier to inspect 100% of all outbound shipments.
2. The receiving organization can sample and inspect a percentage (<100%) of all inbound shipments from the failing vendor.
3. The focal organization and supplier can work together and develop a better production system at an alternative location.
4. Qualify and employ an alternate vendor.

While not a complete list of alternatives, the objective is to evaluate various safeguards to determine if any are an appropriate method to mitigate the prioritized risk source. Below we discuss various mitigation tactics: operational, financial, and organizational countermeasures.

Operational countermeasures, such as inventory buffers and redundant capacity, allow organizations to offset the impact of many categories of disruption. Most practitioners and academics consider operational tactics appropriate when risks and decisions about the various options are understandable. Research indicates that

operational countermeasures facilitate mitigation of catastrophic risks when both the probability of disruption and the estimated losses are high (Knemeyer et al., 2009). (e.g. The American Red Cross prepositions drinking water and medical supplies before large hurricanes make landfall) Such mitigation tactics are appropriate and commonplace within many industries.

Second, financial countermeasures specify monetary compensation for lost sales resulting from a SC disruption. Within the agriculture industry, farmers regularly purchase crop insurance to guarantee revenues against wind and hail damage. While less common than operational countermeasures, financial mitigation techniques provide insurance within certain contexts.

Third, RM experts argue that certain organizational practices may be useful as mitigation techniques (Simchi-Levi, 2010). This strategy suggests incorporating a SC disruption orientation into daily work routines and purposefully aligning an organization's business and RM strategies. For instance, a recent study found the use of training, quality certification programs, and long-term alliances helped reduce supply uncertainty within purchasing organizations (Smeltzer & Siferd, 1998). By employing organizational countermeasures, executives are able enrich their organization by developing internal competencies and external capabilities, rather than investing in RM countermeasures that may never be used.

We recommend that risk managers should evaluate each mitigation tactic to determine its utility as a risk-reducing mechanism against both the risks and consequences evaluated in the assessment step. We argue the mitigation phase needs to

be robust enough for use with both major and minor disruption scenarios and allow practitioners to mitigate various threats with three types of countermeasures: operational, financial, or organizational.

Using our proposed methodology, practitioners should evaluate each ranked consequence against the disruption management framework. For example, a manager would categorize a disruption such as a machine breakdown (risk source)/line down (consequence) in the risk and loss mitigation quadrant because both the probability of occurrence and the predictability of the consequences are high. After categorizing the various threats, practitioners may address the risks and consequences individually or as a group. For example, if seven out of ten threats align with the agility quadrant, managers may assess and select a mitigation strategy simultaneously for the subgroup of seven. Grouping threats by consequential outcome allows managers to identify generic countermeasures that are applicable to multiple disruption scenarios. This would include countermeasures such as a command center, satellite phones, or robust emergency response protocols.

We expect that most organizations will have ranked consequences that fall into multiple quadrants within our framework. When this occurs, managers should adopt multiple SC strategies. For example, safety stock can offset regular power outages, while production flexibility can mitigate scenarios such as floods. Production lines, locations, or divisions within a company may require separate SC strategies. Further, in some case a single facility may require multiples strategies.

### *Responsiveness*

In a typical risk management process *Response or Responsiveness* represents the last step, during which organizations develop methods to respond to disruptions once they occur and to reduce the amount of time the supply chain is affected (Sodhi et al., 2012; ). Practitioners use responsiveness or response capabilities to coordinate and deploy resources to overcome the slowing or stoppage of operations (Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007). As an illustration, switching from foreign to local suppliers, when a disruption has slowed the SC, allows organizations to move, raw materials quickly into production and reinstate operations. Some companies do not develop their recovery capabilities proactively, because they do not plan for SC consequence, but instead only focus on risk sources, and thereby oversee the options in terms of consequence response.

Consequently, we agree that when organizations develop their response capabilities, they should be able to reduce the amount of downtime due to a disruption. Utilizing our framework, the RM team will have explained the various disruption sources and consequences in detail. Practitioners then can utilize our enhanced disruption management framework to choose an appropriate SC strategy that is directly based on the probabilities and resulting consequences of various disruption scenarios. Therefore, respondents can develop procedures in advance and refine them with practice and feedback. For example, when employing a strategy of SC flexibility, organizations must

learn how to move production capabilities between locations. Practitioners can practice change-outs (movement between lines) to determine the most cost effective and efficient method.

After reviewing the four key steps found within most RM processes along with the contributions of seminal articles covering SC risk and BCP, we propose a model to manage and mitigate SC disruption risk. In particular, our framework investigates how the *predictability of consequences* affects the supply chain strategy utilized to offset disruption risk. Adding this dimension to a RM framework is important, because, while the sources of a risk may be predictable based on available probability estimates, the variation associated with the consequences may render specific mitigation tactics ineffective. For example, the United States Army Corps of Engineers built levees around New Orleans based on the size of potential hurricanes (risk source), not the tidal surge (disruption consequence). With insight into the consequences of flooding, the Corps of Engineers may have developed a different disruption management strategy.

### **Disruption Management Framework**

We introduce a disruption management framework that incorporates both the probability of disruption and the predictability of consequences (Figure 2). While the probability of disruption is standard amongst many RM models, the predictability of disruption consequences (vertical axis) represents the inherent variation of consequences that result from a SC disruption. By incorporating these two dimensions within a single

framework, we evolve the conventional RM model and encourage practitioners to learn about the manifestations of a SC disruption and then incorporate that perspective into future countermeasure selection and mitigation processes.

Managers can then navigate between the two dimensions (probability of disruption and the predictability of consequences) and select one of four SC strategies: *supply chain flexibility*, *risk and loss mitigation*, *supply chain resilience*, and *supply chain agility*.

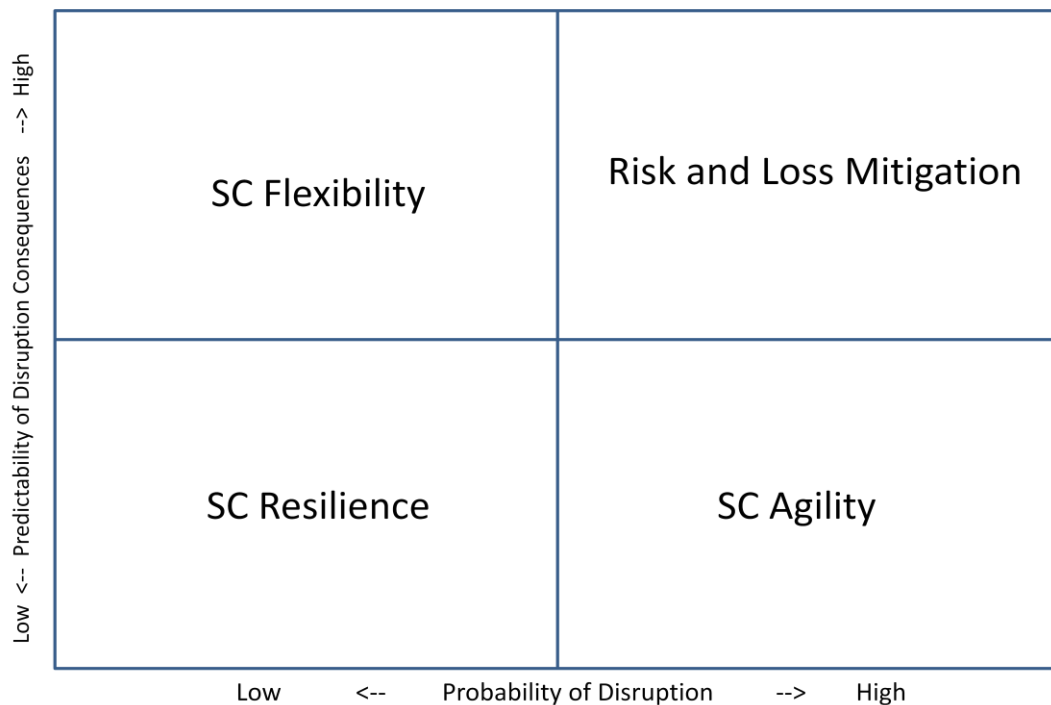


Figure 2: Proposed disruption management framework.

## **Supply Chain Flexibility**

*Supply chain flexibility* explains how organizations react and change the direction of operations without affecting (or minimally affecting) the amount of time, effort, or performance required (Upton, 1994). This definition suggests that practitioners can quickly reconfigure SC to support new offerings, partnerships, and market demands.

In our model, the upper left quadrant of our framework reflects scenarios where the probability of disruption is low and the predictability of the resulting consequences is high. Examples of such disruptions sources include a flood or the failure of a commodity-providing vendor. Both events result in consequences such as the closing of a distribution center or the shortage of key components. When the probability of disruption is low, practitioners regularly take a conservative tact towards RM and may avoid making decisions about mitigation tactics. Committing resources to offset infrequent events is inherently risky from a financial perspective. There is a good chance that managers are wasting both time and money to assess and deploy countermeasures, since the mitigating resources may never be used.

However, because managers can predict the consequences of disruption, organizations are able to develop flexible back-up systems that engage only when needed. In a situation such as a flood (risk source), managers are able to accurately discern the consequences to an organization's supply chain. For example, if flooding is a concern for a production facility, the resulting consequence is that production may have to cease if a flood occurs. Likewise, if flooding is a concern for a distribution center then



trucks will be unable to pick up products and deliver them to customers. In both situations, the consequences are predictable, that is specific items will be unavailable for a limited amount of time (we assume that most floods are short-term events). With this knowledge, managers can build flexibility into the SC and maintain a smooth flow of goods. Research has shown that a small amount of flexibility helps the SC garner much of the benefits of 100% flexibility (Cachon and Terwiesch, 2009). Honda does this by building the Civic at their Alliston, Ontario and East Liberty, Ohio production plants (Niedermeyer, 2008). Even if one of the locations is more economical, the redundancy allows Honda to protect the production capabilities of one of their best selling automobiles.

The failure of a commodity supplier is also a type of disruption suitably addressed by SC flexibility. In this situation, the probability of failure is lower for a commodity supplier than for an innovative supplier, yet the consequences associated with the disruption are more predictable. That is, practitioners need to replace commodity products. When the focal firm creates SC flexibility, by qualifying alternate vendors, it is able to regain quickly a smooth flow of the part.

Demand shaping represents a marketing driven form of flexibility used to offset the consequences of a SC disruption. Specifically, when an organization runs short of inventory, customer service representatives incentivize customers towards the manufacturers' interests. Computer companies, for instance, will offer a deal on an alternate component, such as a larger hard drive, rather than pushing the delivery date

out. Following this logic, we argue that flexibility is the best strategy for SC facing a low probability of disruption and a high predictability of the consequences. The practitioner's conservative stance towards mitigation changes when the predictability of the disruption consequences is included within the risk evaluation process. As managers are able to better discern how the SC will be impacted by a disruption, they can justify investing in certain countermeasures, such as flexibility, with relative confidence.

### Risk and Loss Mitigation

(Knemeyer et al., 2009) used the term *risk and loss mitigation* to describe activities designed to mitigate catastrophic disruptions. While we like this application, we also believe that risk and loss mitigation tactics are appropriate for less severe SC disruptions. There is precedence within the RM literature that supports mitigating threats with lower probabilities. Norrman and Jansson (2004) affirm that mitigation is appropriate when the degree of risk is "medium" or "high," not just "very high." The elevated probabilities imply that the disruptions and the resulting consequences occur frequently enough to establish probability estimates. Disruptions such as machine breakdowns, power outages, and raw material shortages have predictable consequences within an organization's SC.

We advocate the risk and loss mitigation strategy when both the probability of disruption and the predictability of the consequence are high. We argue, however, that this mitigation strategy is also applicable to minor disruptions such as erratic demand. To

address these frequently occurring and highly predictable situations, we suggest that organizations need to adopt a SCRM process that encourages managers to collect and analyze previous disruption data. Accordingly, our framework's upper right quadrant characterizes situations where both the probability of disruption and the predictability of the resulting consequences are high. Because the probability of disruption is high, information and frequency data about disruptions is available. Therefore, managers can evaluate various safeguards (e.g. inventory and/or redundant capacity) and choose countermeasures that support the organization's risk management strategy. In addition, since managers can better predict how the consequences will manifest, they can confidently choose the types and quantities of specific countermeasures'. In the case of a machine breakdown, information about uptime and downtime allows practitioners to calculate appropriate buffer levels, which enable machines to achieve both service level and production cost targets. Many SC textbooks offer strategies to establish exact safety stock targets (Bowersox, Closs & Cooper, 2002). With a SC strategy focused on risk and loss mitigation, an organization is able to address various threats as well as consequences and develop a highly efficient system simultaneously. Thereby, managers can change the way we prepare for frequently occurring disruptions.

### **Supply Chain Agility**

Supply chain agility refers to "the ability to cope with unexpected challenges, to survive unprecedented environmental threats, and to take advantage of changes as

opportunities.” (Sharifi & Zhang, 1999). From the RM paradigm, organizations should use SC agility to cope and adapt to environmental changes created because of a SC disruption. We suggest that when operating in the agility paradigm, managers should account for disruption consequences. Although, the consequences of disruptions are also unpredictable, taking them into account means forcing organizations to design systems and processes so they can be amended when the environment changes. Furthermore, training activities should empower and encourage employees to adjust systems and amend processes when necessary.

Therefore, we recommend that *SC* agility is an appropriate strategy when the probability of disruption is high and the predictability of consequences is low. An unplanned information technology (IT) outage represents a risk source, while email/communication interruptions, delayed orders, and poor customer service are the resultant consequences. When the probability of disruption is high, practitioners confidently commit resources to offset specific disruption consequences, since information about the frequently occurring events is readily available. Frequency data enables managers to evaluate the costs and benefits of specific safeguards.

To address these unpredictable consequences, we also argue that organization should invest in generic countermeasures and organizational adaptation capabilities. Backup generators and redundant communication systems are generic safeguards, while practices such as integration and cross training enhance adaptation capabilities. Dell Computer uses integration to connect with customers and learn about their needs rather

than invest in redundant inventory (Magretta, 1998). Integration, by way of agility, allows organizations to link with partners and learn about customer needs from the relationship.

### **Supply Chain Resilience**

The lower left quadrant of our framework exemplifies situations where both the probability of disruption and the predictability of consequences are low. Cyber attacks, mad cow disease, and terrorist attacks are examples of rare unforeseeable risks that can decimate an organization or negatively affect an entire industry. In these situations, it is difficult to predict any sort of resulting consequence (try to identify the consequences of the 9/11 terrorist attack).

To address these unforeseeable and unpredictable consequences, experts suggest that organizations engage in a high level of cooperation and collaboration, i.e., to share risks with other SC partners (Christopher & Peck, 2004). Such partners might include government agencies and direct competitors, not just suppliers and customers. In 2008, when the craft brew industry faced a worldwide shortage of hops (a main ingredient used in beer production), the Boston Beer Company established a hop sharing program, whereby the company sold hops at cost to the competition (Kroph, 2011). This collaborative relationship supported a budding industry through a potentially devastating period.

When both the probability of disruption and the predictability of the resulting consequences are low, mitigation evaluation techniques fail, as costs will likely surpass any perceived benefits. Therefore, managers will rarely invest in inventory buffers or redundant capacity, since the safeguards may never be used. We believe both the low occurrence probabilities and consequence unpredictability will undermine practitioner's decision confidence.

Recent literature suggests that SC resilience may be the appropriate methodology to address unforeseeable risks, as traditional RM techniques struggle to deal with hard to predict vulnerabilities (Pettit, Fiksel, & Croxton, 2010). To illustrate, during a cyber attack, an organization may have to muster both internal employees and external contractors to restore a severely damaged SC. Resilience is the appropriate approach since managers may not understand where or how to deploy countermeasures (proactively or reactively) within the supply chain.

Following this logic, we assert that SC resilience is a preferred strategy when both the probability of disruption and the predictability of consequences are low. The term *resilience* reflects the ability of a SC to bounce back or quickly adapt to a new standard after a disruption (Rice & Sheffi, 2004). The 2011 Tōhoku earthquake and tsunami that damaged the Fukushima Daiichi nuclear reactor constitutes such a disaster that wreaked havoc for numerous supply chains. Resiliency is favored since these types of disruption will occur infrequently and when they do, it is difficult to predict the effect of the resulting consequences. The disruption characteristics, both infrequent occurrences and

uncertain consequences, create a dearth of information about how to mitigate these disruptions. To address, we argue that managers should develop organizational countermeasure and incorporate a RM perspective into daily work activities. An orientation towards disruption prevention and recovery, prepares employees for the unknown. By purposefully aligning the business and RM strategies, the organization can reinvent itself around its core values (Christopher & Peck, 2004).

## **Discussion**

### **Turbo-Charging the Disruption Management Framework: Warning and Recovery Capabilities**

To improve the fit between the recommended SC strategy and the organization's overall RM policy, we suggest leveraging *warning* and *recovery* capabilities to complement our framework's prescribed SC strategy. Warning and recovery are two risk management capabilities that enable an organization to mitigate the impact of a disruption, altogether eliminate a threat, or potentially capitalize on opportunities that develop because of a SC disruption (Craighead et al., 2007).

#### **Warning Capabilities**

Warning capabilities represent the ability both to *identify* a threat and to *communicate* information about potential or actual disruptions to appropriate parties

(Craighead et al., 2007). Each dimension, identification and communication, requires specific resources and practices to enable the capability. Identification involves scanning the horizon for the sources of a risk or the consequences resulting from a disruption. In certain circumstances, practitioners can identify threats months or years in advance. For example, most organizations that import goods from China are aware of and have plans to mitigate the effects of the 2-week long national Spring Festival (Chinese New Year). The dates of this annual event are set in advance allowing practitioners to plan around this disruption. When an extended warning period is present, existing RM frameworks perform well.

However, other threats, such as a hurricane, are identifiable only days in advance, if at all. The real test for an organization's identification acumen is to recognize a threat and its consequences before the disruption occurs. In December 2009, several US airlines identified a winter storm (risk source) that threatened the holiday travel season. In this case, identifying the threat a few days in advance provided the airlines additional time to assess the situation and devise an appropriate mitigation strategy.

In the best-case scenario, organizations develop identification (*identify*) abilities that allow them to categorize risks and consequences before they happen. To increase the amount of time between identification and disruption, practitioners must identify threats early by scanning the SC horizon for potential sources of risk. A longer warning period provides organizations the opportunity to address, in many cases, both the sources and consequences of a SC disruption. Alternatively, in the worst-case scenario, an



organization discovers a disruption after it occurs. This is the reality when organizations cannot preemptively identify disruptions such as a fire or an earthquake. In this situation, the best possible outcome is to detect the consequences of disruption immediately after it occurs. Stated differently, the best the organization can do is to shorten the time between when a disruption occurs and when someone detects it. Advanced detection capabilities allow an organization time to mitigate the consequences of disruption. Businesses, for instance, can monitor the bond rating and stock market price of suppliers to determine the risk of bankruptcy. If managers predict that a supplier has financial difficulty, alternative vendors can be qualified and selected before the consequences of an actual disruption affects the SC or its partners.

The second dimension associated with warning capabilities is the ability to disseminate information (*communicate*) about a potential threat or the consequences of an actual disruption to all affected parties. Risk managers must communicate information so internal and external partners can understand the context of a disruption and initiate response activities. Internally, organizations need processes and linkages that communicate decisions about credible threats and mitigating actions to others within the organization. The objective is to ensure that all employees are working towards the same goal.

Organizations must also be capable of disseminating information about credible threats and action plans to customers and external partners. Using the airline/winter storm illustration from above as an example, most major carriers flying to the region waived

ticket change fees for customers potentially affected by the storm. In this situation, the airlines communicated their intentions through postings on their website, network television announcements, and direct email notifications, when feasible. This allowed customers to adjust travel plans before the storm actually manifested.

Further, regulatory and other governmental agencies may also require attention during certain SC disruption. Organizations may need additional resources and communication processes in place to ensure compliance when the law mandates a product recall or some such specific action.

By developing appropriate scanning and communication abilities, an organization can enhance its warning capabilities, which reduces the time it takes to address properly the consequences of a SC disruption. Within the context, we believe that enhanced warning capabilities, will improve all four SC strategies recommended by our disruption management framework. Scanning provides information so managers can quickly make decisions about response activities. Then once a decision has been made, communication abilities allow managers to communicate with practitioners responsible for mitigation and recovery.

### **Recovery Capabilities**

Recovery capabilities are either *pre-emptive* or *reactive* interventions designed to return the SC to normal (Craighead et al., 2007). Normal refers to pre-disruption levels where additional personal and resources are no longer required or when managers

reconstitute operations into a new steady state. *Pre-emptive* recovery happens *before* consequences actually manifest. For example, in 2002, a labor issue halted operations at 29 west coast ports. When Dell's management concluded that the port closings were imminent (risk source), the company's logistics team chartered eighteen 747-jet liners. Because Dell reacted earlier than its competitors, the company kept its SC moving at a cost lower than organizations that did not react as quickly (Breen, 2004). Accordingly, pre-emptive recovery efforts allow organizations, like Dell, to mitigate disruption consequences.

*Reactive* recovery occurs *after* a SC disruption actually occurs. A good example of this is when, in March 2000, a small fire (risk source) and the resulting smoke and water damage (consequences) shut down a plant that supplied microchips to both Ericsson and Nokia (Norrman & Jansson, 2004). Nokia immediately contracted with alternate vendors and began re-engineering efforts to accommodate substitute chips. Ericsson, adopting a different strategy, accepted vendor guarantees that the fire would not disrupt shipments. Consequently, Nokia was able to minimize the consequence of the SC disruption and return to a steady state. Ericsson, however, was devastated and could not return to normal for many months. Here, reactive recovery capabilities enabled Nokia, in contrast to Ericsson, to assess the disruption scenario and develop a recovery strategy minimizing the consequence.

When practitioners develop outstanding reactive recovery capabilities, an organization can quickly activate and deploy resources immediately after a disruption occurs. Moreover, managers, in some case, may be able to initiate response efforts before

consequences actually manifest. By deploying the appropriate recovery capabilities, managers can potentially reduce the time between the actual disruption and full recovery.

## Warning and Recovery Timeline

To illustrate how warning and recovery capabilities operate within the RM continuum we introduce a disruption event timeline (Figure 3). The *warning window* is the period between when practitioners authenticate a credible threat and when the disruption occurs. By identifying threats earlier, organizations can increase the warning window. This will extend the opportunity to address the sources of risk and/or respond to the consequences of disruption.

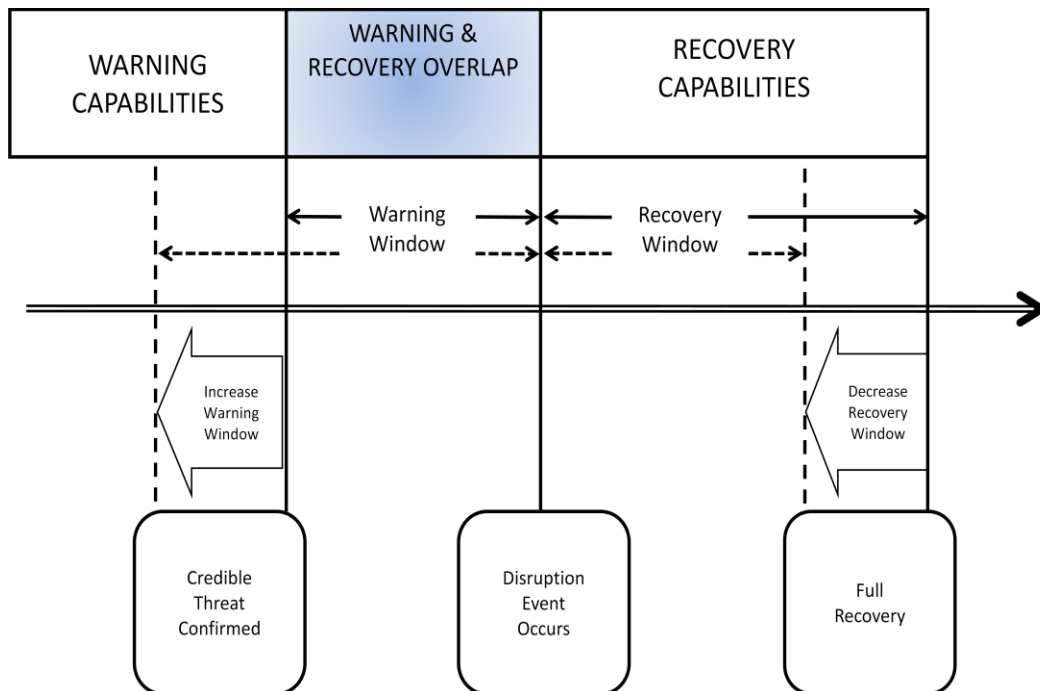


Figure 3: Disruption Event Timeline

We note that, in certain circumstances, there may be no warning window. For example, in March 2011, a 9.0 magnitude earthquake struck Japan. In this case, there was no warning and hence no warning window. Furthermore, an organization may fail to identify a threat altogether. Similar to the situation above, there will be no warning window as no one can authenticate the threat before it occurs. In such scenarios, the only option available to the organization is recovery.

Alternately, we define the *recovery window* as the time between when the disruption occurs and when practitioners achieve full recovery. Full recovery is the threshold where the organization's operations return to pre-disruption levels or aligns to a new normal.

We argue that when an organization develops outstanding recovery capabilities, it can quickly activate and deploy resources after a SC disruption occurs. Managers, in certain situations, may be able to deploy resources before the consequences of disruption manifest. In this case, pre-emptive recovery capabilities allow managers to ready resources and mitigate the consequential affects of a disruption. Further, when practitioners are unable to muster recovery resources before a disruption event, they can deploy them immediately following. By positioning the appropriate recovery resources and protocols, the organization can potentially reduce the time between when an actual disruption event occurs and when achieving full recovery. Both *pre-emptive* and *reactive* response activities allow organizations to reduce the size of the recovery window. Hendricks and Singhal (2003 & 2005) have shown that SC disruptions can negatively affect organizations by up to 40% and linger for years. By developing recovery

capabilities, managers may be able to show that they quickly returned SC operations to normal. Hence, they may be able to lessen the disruptions financial impact.

## **Enhancing the Chosen Supply Chain Strategy with Warning and Recovery Capabilities**

We suggest that managers use our disruption management framework to select one of four SC strategies: *supply chain flexibility*, *risk and loss mitigation*, *supply chain resilience*, and *supply chain agility*. We now describe how managers can enhance their SC and RM strategies by developing an organization's warning and recovery capabilities.

### *Warning and Recovery with Supply Chain Flexibility*

In the *SC flexibility* paradigm, organizations face a situation where the probability of disruption is low and the predictability of consequences is high. This suggests that disruptions are infrequent events, yet managers have a good understanding of the resulting consequences. Previously, we indicated that organizations enable SC flexibility by building alternative states into the production and service systems. This is possible, because the consequences of disruption are predictable, and therefore managers can confidently develop redundant capabilities.

Additionally, since the probability of occurrence is low, organizations will prefer to invest in redundancy across the SC, rather than costly buffers such as inventory. This

is the case, since the probability of utilizing the buffer is low enough to undermine any cost/benefit analysis.

Warning capabilities provide organizations a method to identify and categorize infrequent disruptions/consequences. Practitioners scan reports and the SC horizon for warning signals indicating that threat is building or an actual disruption has occurred. Additionally, recovery capabilities, allow the organization to switch production capacity via standard processes with little loss of time, cost, or performance. Organizations rely on pre-emptive recovery practices to optimize the activities associated with moving resources between various states when an actual disruption occurs. Together, both warning and recovery capabilities strengthen the effectiveness of the flexibility strategy to counter infrequent disruptions with predictable consequences.

#### *Warning and Recovery with Risk and Loss Mitigation*

When the probability of disruptions is high and the resulting consequences are predictable, our framework recommends a strategy of risk and loss mitigation. In this state, both warning and recovery capabilities allow organizations to mitigate the effects of a disruption and reduce the amount of time needed for the SC to return to normal. Scanning activities such as exception reports provide warning signals specific to potential risk sources and actual disruption consequences. These reports act as alerts for out of control conditions and function like a statistical process control system. When warning signals are unavailable, after-action reports and post mortems provide necessary

information to improve pre-emptive and reactive recovery efforts. These practices allow practitioners to accumulate and understand data on the sources of disruption and their resulting consequences. The frequency data and corresponding probability estimates of various consequential scenarios allow managers to make investment decisions about countermeasures and response protocols.

Further, detecting disruption signals is not difficult, due to the relative stability of various threats and consequences. Manager can tune sensing system to recognize specific warning signals in both pre- and post-disruption identification scenarios. For example, the organization can use exception reports and regularly scheduled teleconferences to identify delivery issues with troublesome vendors.

Recovery capabilities reflect the organization's ability to utilize resources and lessen the impact of a disruption and/or reduce the amount of time the SC is affected. Pre-emptive recovery allows the organization to position inventory at predetermined levels before disruption consequences manifest. For example, companies regularly shut down machines to clean and perform maintenance. By pre-positioning buffer inventory, organizations can maintain sales volume during this planned disruption.

Reactive recovery capabilities enable the organization to respond rapidly to a disruption and return the SC to a steady state. These abilities are particularly important when little or no warning period is available. An emergency command center coordinates on-site recovery activities and maintains communications with various parties, including



first responders and government agencies. When linked to a policy of risk and loss mitigation, both warning and recovery capabilities are present

### *Warning and Recovery with Supply Chain Agility*

Our disruption management framework suggests an agile SC when the probability of disruption is high and the predictability of consequences is low. This recommendation is particularly sage for innovative organizations that frequently introduce new products or have products supported by novel processes. In this paradigm, the customer's evolving requirements and accelerated technological change force organizations to prepare for uncertainty by embedding agility into the organization's culture (Sharifi & Zhang, 1999). To accomplish this task, we argue, that organizations should develop both their warning and recovery capabilities. Initially, managers should develop efficient processes that provide end-to-end visibility. Given the unpredictable nature of disruption consequences, practitioners are unable to tune identification and sensing systems to specific parameters. Rather, they must design a screening system that captures a spectrum of potential exceptions that require additional assessment. Once data is collected, analysts can tease out details and make the information compatible with the organization's learning and knowledge transfer systems. This sharing of information allows the organization to become more synchronized and agile as it replaces buffers with information.

Once organizations enable a spectrum of warning capabilities, then they can develop recovery capabilities. Key to both pre-emptive and reactive recovery is the

concept of velocity. As managers identify response strategy, the entire organization may need to adapt systems and/or quickly deploy resources. To enable this, managers should convey the message that agility requires personal flexibility and small batches, rather than economies of scale (Christopher & Peck, 2004; Hamel & Valikangas, 2003).

When embracing a strategy of SC agility, the organization also needs to develop both their warning and recovery capabilities. However, as agile firms work with innovative products that may be more prone to SC disruption, we suggest organizations develop higher levels of warning capabilities as compared to recovery capabilities. This is the case, as employees will regularly leverage identification and communication practices as they work to understand what is happening and which recovery actions are necessary.

#### *Warning and Recovery with Supply Chain Resilience*

Our disruption management framework recommends a strategy of SC resilience when both the probability of occurrence and the predictability of the resulting consequences are low. We suggest that organizations need both their warning and recovery capabilities in order to face unpredictable scenarios with unforeseen consequences.

When faced with low probability disruptions that manifest unpredictable consequences, organizations should leverage their warning capabilities to identify and

educate the employees about specific disruption events. Because these events are infrequent, practitioners will find it difficult to predict the circumstances surrounding the source of a threat or their resulting consequences, as statistical data is unavailable. In addition, once identified, risk experts will continue to expend time and resources to discern the root cause and resulting consequences. Organizations must also utilize their warning capabilities to communicate information about threats to SC partners. Pertinent information should be accurate, visible, and accessible to suppliers, customers, government agencies, and employees throughout the organization (Christopher & Lee, 2004).

Organizations also need to develop and enable a variety of recovery capabilities. Resiliency experts advocate a strategy where employees continuously anticipate, adjust, and reinvent the organization based on core values (Hamel & Valikangas, 2003). This implies that managers marshal financial, physical, and human resources to minimize the negative impact of the resulting consequences. Taken together, practitioners can bolster the SC resiliency strategy by developing both warning and recovery capabilities across the organization. When aligned with the overall operating strategy, managers can leverage these capabilities to strengthen the resilience tactics and mitigate the effect of infrequent disruptions with hard to predict consequences.

## **Conclusion**

After reviewing the relevant SC and RM literature, we identify three gaps associated SC disruption management. First, practitioners need a framework that incorporates the predictability of disruption consequences. There is scant reference within RM literature that explores how disruptions manifest themselves. By including the consequences of disruption, practitioners are better able to understand threats to their supply chain.

Second, practitioners need a methodology, which aligns the organization's risk characteristics and SC strategies. This follows the advice of several experts who suggest developing a RM strategy based on the characteristics of the SC environment (Juttner, H. Peck, & Christopher, 2003; Kleindorfer & Saad, 2005, Manuj & Mentzer, 2008). We believe that by aligning the RM and SC strategies, organizations can better leverage existing resources.

Third, practitioners can use warning and recovery capabilities to bolster the organization's SCRM strategy. Aligning specific RM capabilities with the SC strategy speaks to the "fit" between the organization's decision environment and the mitigation and recovery strategies used throughout the supply chain (Kleindorfer & Saad, 2005).

In order to address these gaps and develop a comprehensive SCRM process, organizations should develop strategies to mitigate the risks associated with a threat and

reduce the amount of downtime after a disruption occurs. Most models explore SC risk by investigating the sources of disruption or risk drivers identified. While informative, these frameworks fail to incorporate a key aspect of SC risk. In particular, few models seek to understand the consequences associated with the actual SC disruption.

Our framework provides a method to understand SC risk by incorporating both the probability of disruption and predictability of the resulting consequences. Practitioners may utilize the model to identify an appropriate SC strategy, which offsets the inherent nature of uncertainty associated with a specific risk profile. We then discuss how managers should develop warning and recovery capabilities as a method to improve the fit between the RM process and the organization's SC strategy. When incorporated into a comprehensive RM process, our framework provides guidance on how to approach disruption threats and helps organizations align their RM, SC, and overall operating strategies.

If managers work to align their SC and RM strategies and then develop an organizations warning and recovery capabilities, they will bolster an organizations overall RM capabilities. In essence, they are creating an organizational culture that encourages practitioners to consider SC threats and disruptions regularly.

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# MEASUREING WARNING AND RECOVERY CAPABILITIES: CONSTRUCT DEVELOPMENT AND MEASUREMETN VALIDATION

## Abstract

Risk management experts suggest developing a comprehensive supply chain risk management strategy that lowers occurrence probabilities, reduces the impact of disruption, and minimizes recovery times so the supply chain can quickly return to a steady state. However, after an extensive review of existing risk management literature, we find most academic research addresses supply chain risk with redundant inventory and/or capacity. While these buffers are appropriate with some supply chain disruptions, both practitioners and academics familiar with risk management techniques agree that organizations should use a variety of techniques to mitigate supply chain risk as threats manifest in various manners. Besides inventory, redundant capacity, and insurance, the literature suggests embedding behavior-based risk mitigation tactics into the organization's culture.

The purpose of this study is to examine how four behavior-based competencies affect the organization's risk management and performance capabilities. We posit that these antecedent competencies improve the organization's risk management and performance capabilities by strengthening the employees' orientation towards supply chain risk. We also develop psychometrically valid measures for two new risk management capabilities: *warning* and *recovery*. Using qualitative interviews, a judgment-based item-to-construct sorting process, and confirmatory factor analysis, we establish the reliability and validity of the new measures.

Empirical results indicate that a *common vision*, *organizational learning*, and *supply chain disruption orientation* enhance an organization's warning and recovery capabilities. Therefore, managers should develop these cultural competencies as a method to improve the organization's risk management acumen. The evidence also suggests that managers must manage *routine rigidity*; otherwise, the competency may undermine the practitioner's ability to sense and respond to supply chain disruptions. We also find that organizations with heightened recovery capabilities have enhanced performance. Together, this indicates that organizations can develop behavior-based risk management techniques and include them as part of the overall supply chain risk management strategy. We argue that this a better way of managing SC risk because it broadens the risk management approach and works to develop the employees' abilities, rather than just investing in rarely used buffers and capacity.

## **Introduction**

While research supports the use of behavior-based practices (e.g. Choi and Liker, 1995; Krause, 1999; Braunscheidel and Suresh, 2009), we find that most RM literature leverages mathematical models or conceptual frameworks. Risk management (RM) experts assert that organizations can use any number of techniques including buffers, capacity, insurance and/or behavioral tactics to manage and mitigate supply chain risk (SCR)., whereby each factor has its advantages and limitations, we argue that behavior-based practices are the most often undervalued, and yet fill a gap that other RM strategies leave open. Behavior-based practices refer to processes, activities, and management initiatives designed to lessen a threat's impact (Eisenhardt, 1989). Managers design the practices to influence behaviors not outcomes. Basically, a process should incentivize practitioners to seek out operational outcomes that are aligned to a higher-level strategic objective (Zsidisin & Ellram, 2003).

Experts suggest that academics are reluctant to investigate behavior-based SCR practices because it is “perceived to be riskier than conceptual or mathematical research” (Sohdi, Son and Tang, 2012, p11). We explore these behaviors because we believe they can be used to augment most other RM strategies including ones where inventory and redundant capacity are not cost effective. For example, a disruption like the 9/11 terrorist attack is both rare and catastrophic in nature. Here behavior-based RM techniques, as compared to a buffer such as inventory, enable practitioners to adjust to the circumstances of specific disruption consequences and drive towards returning the SC to a steady state.

We also believe a lack of valid and reliable measures makes it difficult to conduct behavior-based RM research. Only a few operations management researchers have developed reliable risk measures, including Ellis, Henry, and Shockley (2010) who operationalized measures for the magnitude and probability of supply disruption. Likewise, Tucker (2004) categorized interruption, delay, risk, and losses as dimensions of failure and measured actions that affect nursing patient outcomes. By developing new measures, we fill this gap and allow managers to benchmark their RM capabilities against established targets.

Therefore, we investigate behavior-based competencies and capabilities as a method to manage SCR. These techniques allow managers to develop the processes and practitioners associated with SC and RM activities. When properly embedded, these tactics influence the processes associated with an activity, rather than just the outcome(s) (Anderson and Oliver, 1987). Thus, when managers develop their RM strategy they are investing in the organization's employees and structures, not just resource intensive and rarely used measures like inventory or capacity.

We also aim to operationalize two empirically valid RM measures: *warning* and *recovery* capabilities. *Warning* capabilities speak to the organization's ability to scan the SC horizon for threats and then communicate information about those threats to partners (Craighead et al., 2007). *Recovery* refers to pre-emptive and reactive response tactics enabling the organization to return to the SC to normal (Craighead et al., 2007). After operationalizing the measures, we answer three research questions: First, do warning and recovery capabilities explain organizational performance? Second, do certain

competencies affect the behavior-based warning and recovery capabilities? Finally, does information quality mediate the relationship between the antecedent competencies and the RM capabilities? By answering these questions, we intend to show that managers can develop behavior based competencies and capabilities as a means to enhance an organization's RM acumen and performance.

To address these questions, we develop measures for warning and recovery capabilities. We empirically validate the questions and the survey instrument using qualitative feedback multiple item-to-construct sorting procedure (Q-sort), confirmatory factor analysis (CFA), and survey data collected from procurement professionals.

Once measures are developed, we examine the linkages between the four competencies: common vision, supply chain disruption orientation (SCDO), organizational learning, and routine rigidity, and the two RM capabilities, warning and recovery. By investigating both the direct and indirect linkages between the internal competencies and external facing capabilities, we provide evidence about the affect of specific behavior-based competencies as RM devices. For the indirect effects, we look at the mediating variable information quality. By researching how the information quality of messages affects the relationship between the competencies and RM capabilities, we provide guidance for managers as they communicate with practitioners throughout the organization.

Lastly, we investigate the relationships between the warning and recovery capability constructs and organizational performance. Specifically, we establish a linkage from the four competencies, through the two RM capabilities, to organizational

performance. This provides evidence about how the RM capabilities affect the overall organization. Without evidence supporting this relationship, managers may not value behavior-based practices as part of their RM strategy.

### **Outline of the manuscript**

We review the extant RM, SC, and high reliability theory literature and define our terms in section 2. In section 3, we introduce an initial model and specific hypotheses. Within section 4, we attend to the methodology and statistical analysis. In section 5, we introduce an alternate model supported by concise hypotheses. We devote section 6 to our research findings and a discussion of pertinent limitations. Finally, in section 7, we conclude with future research opportunities and predictions of how our theory changes the culture of SCRM.

### **Literature Review**

In the following section, we establish the theoretical foundation for our study of behavior based SCRM practices. We introduce high reliability theory and then discuss risk, supply chain risk, and supply chain risk management. Lastly, we review warning and recovery capabilities and converse about the various dimensions reflected within the two RM constructs.

## **High reliability theory (HRT)**

We leverage *high reliability theory* (HRT) as our theoretical lens as it provides a framework on how to operate a complex system such as a SC safely and profitably. Proponents of HRT theory argue that organizations can stave off accidents indefinitely by designing and managing systems that emphasize reliability rather than just efficiency. Rochlin, LaPorte, and Roberts (1987) coined high reliability theory when describing how aircraft carriers could operate safely in the face catastrophic risks. Early high reliability researchers investigated aircraft carriers (Rochlin et al., 1987; Weick and Roberts, 1993), submarines (Bierly and Spender, 1995), and nuclear power plants (Roth, 1997). Now researchers use the theoretical frame for lean management (Marley, 2006), emergency decision-making (White, Turoff, and Van de Walle, 2007) and SC safety research (Speier, Whipple, Closs, and Voss, 2011).

Researchers classify an organization as highly reliable when it is able to maintain an exemplary safety record over long periods (Roberts, 1990). Hence, highly reliable organization's "are complex systems in which many accidents and adverse events that could occur within those systems or at the interfaces with other systems are actually avoided or prevented" (Bagnara, Parlangeli, and Tartaglia 2010, 713). While reliability from an engineering perspective refers to a component or system that performs repetitively, high reliability focuses on the continuous management of fluctuations (Weick, Sutcliffe, and Obstfeld, 1999). Hollnagel (1993) views this formulation of reliability as an extension of adaptive human cognition and action research.

While some advocates stress systems reliability above all else, for most highly reliable organizations the goal is a combined state of performance and safety (La Porte and Consolini, 1991). The danger associated with these systems force organizations to go to great lengths to avoid failure. To achieve this goal, managers design the organization around resiliency and redundancy, manage in a decentralized manner that encourages improvisation, and develop a culture that encourages employees to make decisions when necessary (Weick et al., 1999). In addition, mindful practitioners manage these systems by learning from errors/near misses and avoiding simple interpretations that lead to mishaps (Weick et al., 1999).

Several of the theory's characterizations align with the aims of this investigation. Initially, we seek to understand how antecedents, such as common vision, supply chain disruption orientation, organization learning, and routine rigidity, affect the proposed warning and recovery capabilities. We believe these competencies are similar to key high reliability theory characterizations. Common vision and SCDO, for instance, speak to the beliefs the management embed into the organization's culture. Common vision represents the management's view on strategic goals, while SCDO reflects the SC operational objectives. When embedded correctly, employees derive energy and purpose to pursue strategic (common vision) and operational (SCDO) objectives (Braunscheidel and Suresh, 2009).



## **Supply chain risk**

Before we can talk about SCR, we need to define *risk* itself. *Risk* refers to the probability and significance of a loss that affects an individual or organization (Harland, Brenchley, and Walker, 2003). Managers should note risks “that can modify or prevent part of the movement and efficient flow of information, materials and products between the actors of a supply chain within an organization or among actors in a global supply chain” (Lavastre, Gunasekaran, and Spalanzani, 2012, p. 830).

Tangential to the notion of risk is the concept of risk taking. Ho (1996) investigates risk taking to understand how managers perceive risk (risk taking, risk neutral, or risk averse) when making decisions about manufacturing strategy. Risk taking reflects the manager’s beliefs about the riskiness of the environment. Similarly, Jambulingam, Kathuria, and Doucette (2005) measure strategic risk taking in the service environment. Here, risk-taking represents the manager’s orientation towards taking action to achieve organizational goals. The researchers, in both investigations, assume that the risk taking posture of managers influences the organization’s strategy and future direction. We support this logic and argue that the perceptions of risk, rather than just objective measures, drives behavior when making decisions about future operations (Ellis et al., 2010).

*Supply chain risk* (SCR) refers to unplanned and unpredictable events that negatively affect one or more parties within a supply chain (Deloitte, 2004). These variations can affect “the information, material, and product flows from original supplier to the delivery of the final product for the end user” (Juttner, Peck and Christopher, 2003,

p.203). Risks are classified in many forms including natural and manmade (Sheffi, 2009), low probability-high consequence (Knemeyer, Zinn, and Eroglu, 2009) and internal and external (Christopher and Peck 2004). Furthermore, some researchers categorize SCR into risk types: organizational, network, and environmental (Jüttner et al., 2003).

Organizational risks result from information technology, labor, and production uncertainties. Network risks develop because of poor integration between SC partners. Environmental disruptions result from natural disasters and socio-political uncertainty.

### **Supply chain risk management**

*Supply chain risk management* (SCRM), describes how organizations and SC partners manage risks through a coordinated approach to reduce the impact of threats (Cranfield,2003). RM experts suggest developing systems that avoid, postpone, mitigate, hedge, control for, or transfer risk to others (Manuj and Mentzer, 2008). Organizations must also account for the risk-seeking or risk-adverse attitude of practitioners managing SC processes (Manuj and Mentzer, 2008). Research suggests that risk attitudes affect the RM strategy selected and the risks taken by an organization. For example, Pablo (1999) found that managers view and interpret risk differently depending on industry. When taken together, an organization's SCRM strategy should attempt to both reduce the probability of occurrence and the impact of disruptions. After reviewing the extant literature, we believe there is not a single strategy to mitigate all SC risks. Therefore, we recommend that managers should develop several strategies that address potential risk, complexity, and overall SC goals.

### **Warning capability**

One of the key SC capabilities we focus on in this study is *warning capability*, which refers to coordination of resources to scan for, detect, and communicate information about pending or actual SC disruptions (Craighead et al., 2007). When practitioners scan for and identify threats, they should use available time to assess the probability of occurrence and the impact of resulting consequences. Organizations can then deploy the appropriate mitigation and recovery resources and communicate actions to other SC partners.

Communication capabilities speak to the organization's information sharing abilities. We suppose that communication activities are important as they enable practitioners to prepare for and recover from a SC disruption. This occurs as the organization and its SC partners are able to initiate response strategies or communicate changes about specific actions to partners.

### **Recovery capability**

The second capability pivotal to our study is *recovery capability*, which reflects an organization's ability to mitigate the impact of a disruption and to decrease the time it takes to return supply-chain functions to normal. Normal refers to a state where operations return to pre-disruption levels or a new standard brought about by circumstances and managerial directive. Further, Craighead et al. (2007) divide recovery capabilities into two components: pre-emptive and reactive. *Pre-emptive* recovery extols

collaboration and coordination efforts before a SC disruption occurs, while *reactive recovery* alludes to post-event response efforts.

#### *Pre-emptive recovery*

Organizations can identify threats before a SC disruption manifest, which defines *pre-emptive recovery* strategies. When this occurs, managers may be able to mitigate the impact of a disruption or eliminate a threat altogether. We define mitigation as actions designed to reduce the consequences of a disruption. The reduction potential depends on the type of disruption, consequences anticipated, resources marshalled, and the amount of time until the disruption occurs. We note that pre-emptive recovery differs from warning capability, as the later speaks to identification or communication capabilities..

#### *Reactive recovery*

Craighead et al. (2007) define *reactive recovery* capabilities as the coordination of physical and human resources to overcome the slowing or stoppage of the supply chain. After a disruption occurs, we submit that organizations actively work to return their SC operations to normal. Thus, practitioners will collaborate with SC partners and coordinate recovery resources, in efforts to minimize recovery times.

The consequences of disruption can occur immediately after a disruption manifests or after some time has passed. Hurricane consequences, for example, occur in phases. Initially wind generates damage before the actual storm makes landfall, while

storm surge inundates the shoreline as the hurricane moves from ocean to land. Finally, depending on the movement of the storm, additional inland flooding can occur.

### **Proposed Model and Hypothesis Development**

The conceptual tenets of high reliability theory frame the hypothesized relationships found within our proposed model (see Figure 1).

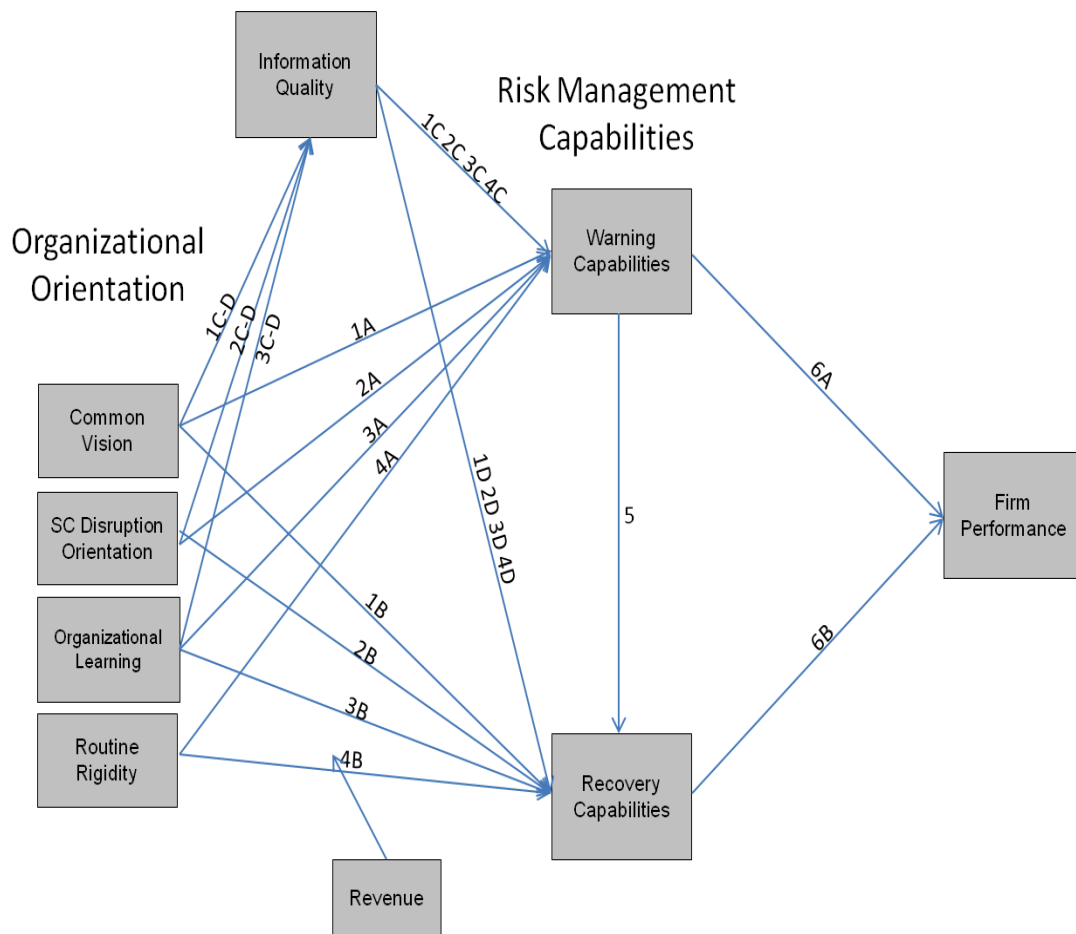


Figure 1- Base Model

## **Theoretical model**

We develop a theoretical model that has four antecedent competencies, one mediating variable, two RM capabilities, and organizational performance. The four antecedents, common vision, SCDO, organizational learning, and routine rigidity, represent competencies that inform the organization's orientation and culture. Warning and recovery reflect organizational RM capabilities. Information quality mediates the relationship between the intra-organization competencies and the organizational RM capabilities. Lastly, organizational performance serves as a proxy for financial and operational performance.

## **Proposed relationships**

We will now define these terms within the literature to gain a conceptual foothold to better understand what is to follow, our proposed relationships and mediations between the competencies, capabilities, and performance.

### **Common vision (CV)**

*A common vision* is collection of high-level objectives, which provide employees with purpose and energy to pursue the organization's goals (Braunscheidel and Suresh, 2009). Executives should embed the common vision into the organization's culture, so employees can commit to these high-level objectives without direct incentives. To do so, executives communicate the common vision and their beliefs about why the vision important on a regular basis. "Sharing and communicating a common vision is the first

step in lasting change, but to be more than just words, it must be married with proper support and regular monitoring” (Dillon, 2010, p. 18).

### **Supply chain disruption orientation (SCDO)**

*A supply chain disruption orientation (SCDO)* speaks to an attitude or organizational characteristic concerning how thinking about and managing risks can minimize downtime and improve performance during SC disruptions. Bode, Wagner, Petersen, and Ellram (2011) refer to SCDO when describing an organization’s general awareness, concern for, and recognition of SC disruptions. Pertaining to the warning construct, SCDO reflects an employee’s alertness and preparedness. This includes the way practitioners seek out and communicate information about SC threats. For recovery efforts, SCDO feeds response practices both before and after disturbances occur.

### **Organizational learning (OL)**

*Organizational learning* refers to the way internal employees learn from experiences (Sinkula, 1994). Said differently, as positive and negative interactions occur, organizations use learning routines to transform their experiences into knowledge, so new understanding alters the way the organization conducts itself in the future.

### **Routine rigidity (RR)**

Gilbert (2005) discusses routine rigidity when decomposing organizational inertia. The concept suggests that during periods of disturbance, the inertia of the

organization inhibits adaptation and undermines employee's response efforts. Zimmermann (2008), for instance, describes how the New York Stock Exchange executives refused to change when electronic trading threatened the exchange's existence. Zimmermann found that managers clung to traditional routines, rather than embracing automated electronic trading. Hence, employees entrenched themselves and adhered to what they knew, rather than developing strategies to address threats. Said differently, practitioners hesitate as they are uncertain about how to respond, or if they have the authority to respond.

### **Information quality**

*Information quality* refers to the accuracy, completeness, timeliness, reliability, and adequacy of data and/or information (Monczka, Petersen, Handfield, Ragatz, 1998; Li and Lin, 2006). Instruments measuring information quality seek to understand message quality as they pass between two entities such as employees (Zhou and Benton, 2007). Research has shown that information quality degrades as time passes between creation and consumption (Feldmann and Müller, 2003; Mason-Jones and Towill, 1997). Opportunism drives practitioners to distort, disguise, or otherwise obfuscate transaction information (Williamson, 1985). "To reduce information distortion and improve the quality of information shared, information shared has to be as accurate as possible and organizations must ensure that it flows with minimum delay and distortion" (Li and Lin, 2006, p. 1643).



The four competencies, common vision, supply chain disruption orientation, organizational learning, and routine rigidity, reflect organizational orientations and represent the social learning mechanisms that help align the top management's view to lower level operational activities. (Atuahene-Gima and Ko, 2001). With high reliability theory as our theoretical lens, we suggest managers can manipulate the competencies to affect an organization's ability to learn from mistakes and near misses (Weick et al., 1999). Hence, we submit that managers can direct the organization's orientation and influence business outcomes. By extension, we reason that learning enables a positive change in behavior (Sinkula, 1994).

#### **Formal hypotheses: Relationships with SCRM capabilities**

Leveraging the generally accepted paradigm that competencies are antecedents to capabilities (Prahalad and Hamel, 1990; Roth and Jackson, 1995), we hypothesize that three competencies, common vision, SCDO, and organizational learning, positively influence warning and recovery capabilities. We further suppose that routine rigidity negatively influences both of the organization's RM capabilities.

Within our model, we include information quality as a mediating variable that affects the relationship between three antecedent competencies and the proposed RM capabilities. McDowell and Karriker, (2009) insist that further research is necessary to understand the mediating effect of information quality, as it is an important component of communication and performance practices.

Lastly, model #1 illustrates how the two RM capabilities positively affect performance. We put forth that organizations should develop behavior-based RM capabilities, like warning and recovery capabilities, in order to improve performance. Our perceptual measures serve as a proxy to performance. We now introduce our formal hypothesis and the rational underpinning our arguments.

### **Relationship between common vision and the organizational SCRM capabilities (H1A-B)**

We suppose that the *common vision* provides guidance on how employees should conduct themselves. This applies to established routines used during non-disruptive periods and to situations where practices must be adapted to address an unfamiliar environment caused by a SC disruption. Thus, we postulate that a well-communicated and properly embedded common vision will positively affect both an organization's warning and recovery capabilities.

#### **Warning capability**

When considering *warning capability*, the common vision should shape how employees scan for and communicate information about SC threats. By emphasizing these characteristics in daily activities and messages, employees can commit time and resources to developing these abilities. However, if managers do not call attention to SC threat detection within the common vision, then employees will be less invested and lack

the capabilities to identify or communicate information about SC disruptions. Hence, we propose:

*H1A-Organizations with higher common vision levels will have higher warning capability levels.*

### **Recovery capability**

For *recovery capabilities*, a common vision cultivates the organization's response efforts by encouraging employees to return the SC to normal in the shortest possible time. Additionally, managers should use the common vision to guide employees when they face unfamiliar conditions that manifest because of a SC disruption. Specifically, if management emphasizes that recovery is important to the organization, employees will develop adaptive methods to speed response efforts. This follows Hays and Hill (2001), who suggest that employees embrace experimentation and risk taking when management's guidance is unavailable. High reliability theory proponents highlight the organization's resiliency and its ability to adapt during recovery. However, if managers fail to emphasize response objectives, we believe practitioners will prepare less for SC disruption consequences. Thus, we propose the following:

*H1B-Organizations with higher common vision levels will have higher recovery capability levels.*

**Information quality mediates the relationship between common vision and the organization's RM capabilities (H1C-D)**

We investigate information quality as messages pertaining to the organization's vision, move from executives to employees. Typically, executives communicate their beliefs both verbally and in written form (Baum, Locke, and Kirkpatrick, 1998). If the messages carrying the common vision are high quality, employees will better understand the organization's needs both before and after a SC disruption. Prior research indicates that practitioners will have improved confidence and decision-making capabilities (Raghunathan, 1999). However, if the common vision conveying message has poor information quality, then practitioners may misunderstand their directive. This may delay communication and response activities.

### **Warning capability**

In the warning capability context, high information quality should improve a practitioner's understanding of objectives as they pertain to scanning for and communicating information about SC threats. We hypothesize that managers can influence an employee's understanding of goals by improving the quality of the warning capability messages. In other words, managers can strengthen the relationship between common vision and warning capability by enhancing the quality of communications. Hence, we offer the following:

*H1C-Information quality mediates the relationship between common vision and warning capability.*

## **Recovery capability**

We also put forward that information quality affects the relationship between the common vision and recovery capability constructs. In this context, recovery capability speaks to an organization's ability to respond to a SC disruption. If the information quality of the recovery messages is high, employees will think about and incorporate previous lessons learned into future response tactics. With pertinent information about incidents, practitioners can quicken resource deployment. In addition, clear messages outline the objective of rebuilding the SC in a timely manner. Hence, employees develop practices to hasten response. From this foundation, we offer the following hypothesis:

*H1D-Information quality mediates the relationship between common vision and recovery capability.*

## **Relationship between supply chain disruption orientation and the organizational SCRM capabilities (H2A-B)**

To improve the organization's ability to deal with SC disruptions, research suggests that managers should develop a RM strategy that includes an understanding of the dimensions of SC risk and tune the mitigation approaches to the organization's environment and culture (Chopra and Sohdi, 2004; Faisal, Banwet, and Shankar, 2006). This implies having an orientation towards understanding SC threats and the techniques to mitigate actual disruption. To embed a SCDO into an organization, managers should incorporate a SCRM perspective into operational communications and activities. This includes threat scanning, disruption analysis, and response processes. In addition, the

SCDO should encourage the organization to develop partnerships to deal with risk cooperatively rather than take on SC risk by themselves. Like portfolio theory, in which financiers seek to minimize risk by selecting a variety of offsetting stocks, a group of SC partners can address risk cooperatively. When viewed through the high reliability theory lens, this is designing the SC for resiliency and thinking about SC risks.

When an orientation toward considering SC disruption exists, everyone from the Chief Executive Officer to the mailroom clerk, develops a risk posture and is mindful of potential disruptions. At high levels of SCDO, organizations are active and strive to learn from experiences (Daft and Weick, 1984). Proponents suggest that highly reliable organizations will learn from mistakes by digesting previous experiences and using the knowledge to prepare for future disruptions (Roberts, 1990). Conversely, organizations with low SCDO levels are passive and slow to respond to disruption.

Evidence suggests that by developing their SCDO, organizations can improve their level of preparedness. Bode et al. (2011), for instance, found that a SCDO motivates the organization to seek out buffering and bridging relationships with SC partners. They also found that prior disruption experience affects the SCDO level within an organization. Prior experience refers to the occurrence of a SC disruption within the past 12 months (Bode et al., 2011). Therefore, as the number of events increases, so does the experience level.

### **Warning capability**

We argue that when SCDO levels are high, that organizations are motivated to act. This motivation empowers employees to seek out and make sense of anomalies within the SC (Kleindorfer and Saad, 2005). In the warning context, this occurs when employees communicate regularly with partners or seek to understand information. In essence, SCDO enhances the organization's scanning and communication practices.

Hence:

*H2A-Organizations with higher SCDO levels will have higher warning capability levels.*

### **Recovery capability**

With respect to recovery capability, a SCDO encourages employees to minimize damage and downtime. From this perspective, we suggest that SCDO allows organizations to respond and adapt to the resulting consequences of a SC disruption. Leveraging high reliability theory thinking, practitioners use practice and simulation to refine emergency protocols. Refinement includes better resource placement and the identification of timesaving steps within processes. With infrequently used response processes, practice provides the only hands on experience until an actual disruption occurs.

A key aspect of high reliability theory is a culture that promotes responsiveness and vigilance (Weick et al., 1999). We see this cultural imperative similar to the cautious and observant attitude embodied with the SCDO competency. We believe this posture

allows organizations to respond to and recover from SC disruptions. Hence, we hypothesize the following.

*H2B-Organizaitons with higher SCDO levels will have higher recovery capability levels.*

### **The mediating effect of information quality on the relationship between SCDO and the organization's RM capabilities (H2C-D)**

As the SCDO provides awareness of, concern for, and recognition of SC disruptions (Bode et al. 2011), managers should develop specific goals and objectives on how to address certain SC disruption scenarios. This provides employees a standard to strive for during their daily work activities. Previous research illustrates that when management addresses specific hazards, the larger organization is willing to think about and see hazards (Westrum, 1988).

Additionally, managers should state their support for individual improvisation and employee empowerment. This shows that practitioners can act, without retribution, during a disruption. "If people are blocked from acting on hazards, it is not long before their 'useless' observations of those hazards are also ignored or denied, and errors cumulate unnoticed" (Weick et al., 2008, p.37).

### **Warning capability**

In order for practitioners to understand the SCDO, management should regularly communicate their views about the SC and SC disruption. We state that if the quality of these messages is high, then practitioners who are mindful will have an enriched



awareness and distinctive concern for their organization (Weick et al, 1999). However, if the information quality of these communications is poor, then practitioners may fixate on routine activities without concern for SC disruptions (Weick et al, 1999). From this perspective, we offer the following hypothesis:

*H2C-Information quality mediates the relationship between SCDO and warning capability.*

### **Recovery capability**

We also put forward that information quality mediates the relationship between the SCDO and recovery capability construct. In this case, a message of SC resilience should flow from management to employees (e.g. purchasing, logistics, warehousing, etc.). We define resiliency as the “capacity to cope with unanticipated dangers after they have become manifest” (Wildavsky, 1991, p. 77).

From the high reliability theory perspective, resiliency suggests that organizations and their extended SC absorb the shock of disruption. Organizations do this by forming ad-hoc groups that solve problems when they arise. Management activates these informal groups during periods of uncertainty and allows them to supplement the normal hierarchy (Rochlin, 1989; Bourier, 1996). These groups “allow for rapid pooling of cognitive knowledge to handle events that were impossible to anticipate” (Weick et al, 2008, p. 47).

If the resiliency message from management has poor information quality, then practitioners may fail to form these ad-hoc groupings when necessary. Likewise, potential members, with specific talents and/or knowledge may hesitate to join.

Conversely, if the information quality of messages is high, the ad-hoc groups will form and dissolve as needed. This occurs because employees believe they have management's support to improvise and recombine available recourses to address a SC shock. Hence, we propose the following:

*H2D-Information quality mediates the relationship between SCDO and recovery capabilities.*

### **Relationship between organizational learning and the organizational SCRM capabilities (H3A-B)**

Organizational learning enables practitioners to collect new information and then use the knowledge to change future behaviors so the organization can survive and succeed (Klimecki & Lassleben, 1998). When viewed through an high reliability theory lens, a preoccupation with failure and learning from mistakes/near misses enables practitioners to prepare for SC disturbances by planning for and thinking about disruptions. When managers believe that new practices will benefit the organization, the employee's organizational learning should be nurtured (Leonard-Barton, 1992). Using this frame, we argue that organizational learning also represents the ability to modify behavior, based on new knowledge and/or novel insight.

In the SC disruption context, practitioners leverage organizational learning when new information about disruptions becomes evident. Simulation and stress tests are techniques used to gather information about SC disruptions. Managers utilize output of these tests to develop new approaches for both warning and recovery efforts.

Organizations also learn from actual occurrences, including mistakes.

Practitioners analyze after-action and post-mortem reports to understand what efforts worked and what led to suboptimal outcomes. When practitioners analyze these data, the findings provide information that makes organizations more confident about future actions (Bell, Whitewell, & Lucas, 2002). Therefore, we hypothesize the following:

*H3A-Organizations with higher organizational learning levels will have higher warning capability levels.*

*H3B-Organizations with higher organizational learning levels will have higher recovery capability levels.*

### **The mediating effect of information quality on the relationship between organizational learning and the organization's RM capabilities (H3C-D)**

The concept of organizational learning suggests that organizations extract information from the environment, integrate it into the organization, and then change future behavior. When considering the relationship between organizational learning and the RM capabilities of warning and recovery, we believe that the level of information quality will affect both the speed and depth of which an organization learns. When high information quality is available, we affirm that practitioners can better identify, communicate information about, and respond to SC threats, because they can confidently connect data pertaining to a SC disruption from multiple sources. By improving an analyst's confidence, they are able to make decisions earlier and provide more detail to response agents. This affords time to develop and deploy an appropriate response

strategy, which may mitigate or even eliminate the SC threat altogether. When information quality is poor, we assert that practitioners will hesitate to amend current warning or recovery practices. From a high reliability theory perspective, information quality is an important antecedent to “evidence based decision making” and “individual improvisation.” Without quality information, practitioners may hesitate at the most crucial moment. From this position, we offer the following hypotheses:

*H3C-Information quality mediates the relationship between organizational learning and warning capabilities.*

*H3D-Information quality mediates the relationship between organizational learning and recovery capabilities.*

We note that the base model also contains additional relationships that we do not explore at this time. For example, there is a three-path relationship from common vision to INFOSHR to WARN and then to PERF. Both INFOSHR and WARN mediate the relationship.

### **Relationship between routine rigidity and the organizational SCRM capabilities**

#### **(H4A-B)**

Next, we discuss routine rigidity, a term coined, along with resource rigidity, as a dimension of organizational inertia (Gilbert, 2005). In this context, routine rigidity described how practitioners within organizations were unable to change behaviors when

faced with change (Gilbert, 2005). We extend the concept into our research and suggest that practitioners, when facing a SC disruption, are exposed to routine rigidity.

### **Warning capability**

We emphasize that *routine rigidity* inhibits the organization's ability to identify and communicate information about threats to SC partners (internally and externally). This occurs as employees adhere to existing protocols, rather than create unique approaches when faced with the uncertainty of a SC disruption. From this reasoning, we offer the following hypothesis.

*H4A-Organizations with higher routine rigidity levels will have lower warning capability levels.*

### **Recovery capability**

Recovery capability speaks to how an organization responds to a period of discontinuity such as a SC disruption. Routine rigidity is present when employees have difficulty deviating from existing processes. We believe routine rigidity goes beyond individuals pushing back from change. Rather, employees within an organization refuse to experiment with existing processes. Therefore, when discontinuities are present, employees find it difficult to adapt (Teece, Pisano, and Shuen, 1997). Therefore, we offer the following:

*H4B-Organizations with higher routine rigidity levels will have lower recovery capability levels*

#### **Relationship between warning capability and recovery capabilities (H5)**

According to Craighead et al., (2007) when organizations properly uses their warning capability to detect and communicate pertinent information about disruptions, they may be afforded time to inoculate themselves from the negative effects of a SC disruption. Essentially, there is time to develop a mitigation strategy and deploy resources to offset disruptions. Therefore, warning capability also affects the organizations ability to respond to a disruption. Hence, we offer a hypothesis linking the two organizational RM capabilities.

*H5-Organizations with higher warning capability levels will have higher recovery capability levels.*

#### **Relationship between the organizational RM capabilities and performance (H6A-B)**

We evaluated organizational performance with three perceptual measures: market share, operating cost, and service quality. The interviewees involved in the qualitative interviews process confirmed that procurement professionals would be able to respond to perceptual questions about these concepts. Most practitioners consider market share to be a primary business success measure, while operating cost reflects practices designed to improve asset availability, efficiency, and quality (Challis and Samson, 1996). In addition, service quality is a common measure within most organizations. We ask

respondents to rate their organization's market share, operating cost, and service quality as compared to the competition.

### **Relationship between warning capabilities and organizational performance (H6A)**

The high reliability theory literature suggests that by quickly adjusting practices that an organization can maintain its competitive advantage. In this context, warning capability reflects the organizations ability to seek out SC threats and communicate information about the threats to partners. Scanning provides information about disruptions and educates practitioners on how to best respond. This includes the immediate positioning of resources and the long-term development of new capabilities. In addition, organizations communicate information about upcoming disruptions to employees within the organization and to external partners that are unfamiliar with existing strategies and practices. The information embedded within messages should contain enough detail to insure comprehension by the receiving partner.

From this perspective, if an organization has high warning capability levels, we believe that they will be able to scan the SC horizon and allow for the early threat identification. Early identification provides time in which the organization can reconfigure tactics and reposition resources in the effort to thwart pending SC disruptions. Further, we believe that once an organization identifies a threat, that managers can use their communication skills to exchange information about upcoming threats to relevant partners. Therefore, we incorporate the scanning and communication abilities into the warning capability construct and offer the following:

*H6A-Organizations with higher waning capability levels will have higher levels of performance.*

### **Relationship between recovery capabilities and organizational performance (H6B)**

Practitioners should use recovery capability to deploy human and physical resources and develop tactics to mitigate the effects of a SC disruption. Pre-emptive recovery occurs before an actual disruption, while reactive recovery occurs after the disruption becomes evident. According to the literature, high reliability theory enables organizations to learn from previous accidents and near misses and to change future behaviors. To this end, the organization can build and defend its competitive advantage by developing recovery capability better than the competition.

When organizations are able to identify threats before a disruption occurs, they are afforded time to respond. Pre-emptive recovery allows organizations to reduce or eliminate the impact of a SC disruption altogether. Practitioners seek to understand how a threat is manifesting itself and then alters the configuration of resources and operational tactics.

Reactive recovery capabilities enable organizations to react to SC disruptions after they occur. The ability to react quickly is important when a SC disruption event offers no warning or when practitioners are unable to foresee the occurrence. During reactive periods, practitioners evaluate how a threat is manifesting and marshal the appropriate resources to counteract specific consequences. For example, in 1989, work crews repaired the eastern span of the Bay Bridge after the Loma Prieta earthquake



damaged it just over a month earlier (Citizendia.org). The California Department of Transportation executives worked with contractors to determine the quickest way to repair and reopen the earthquake-damaged bridge that transported thousands of commuters daily between San Francisco and Oakland, California.

We incorporate both pre-emptive and reactive response capabilities into the recovery capability construct and offer the following hypothesis.

*H6B-Organizations with higher recovery capability levels will have higher levels of performance.*

We summarize the proposed hypotheses in Table 1 and then describe the methodology employed to operationalize the various constructs and test the related hypotheses.

Item	Hypothesis
H1A	Organizations with higher common vision levels of will have higher warning capability levels
H1B	Organizations with higher common vision levels of will have higher recovery capability levels
H1C	Information quality mediates the relationship between common vision and warning capability .
H1D	Information quality mediates the relationship between common vision and recovery capability .
H2A	Organizations with higher SCDO levels will have higher warning capability levels
H2B	Organizations with higher SCDO levels will have higher recovery capability levels
H2C	Information quality mediates the relationship between SCDO and warning capability .
H2D	Information quality mediates the relationship between SCDO and recovery capability .
H3A	Organizations with higher organizational learning levels will have higher warning capability levels
H3B	Organizations with higher organizational learning levels will have higher warning capability levels
H3C	Information quality mediates the relationship between organizational learning and warning capability .
H3D	Information quality mediates the relationship between organizational learning and recovery capability .
H4A	Organizations with higher routine rigidity levels will have lower warning capability levels
H4B	Organizations with higher routine rigidity levels will have lower warning capability levels
H5	Organizations with higher warning capability levels will have higher recovery capability levels.
H6A	Organizations with higher warning capability levels will have higher levels of performance.
H6B	Organizations with higher recovery capability levels will have higher levels of performance

Table 1: Summary of Hypotheses- base model

### **Instrument Development**

We leverage Noar's (2003) construct development process. Starting with existing definitions and measures, we adapt multiple questions for each construct. TABLE 2 identifies the dimension and originating authors. See appendix A for a complete list of survey questions.

#### **Common vision**

For the common vision measurement items, we draw from existing SC (Spekman, Kamauff, and Myhr, 1998) and logistics research (Stank, Keller, and Closs, 2001/2002). To reiterate, a common vision reflects the strategic alignment of an organization and its suppliers. Managers can improve the organization's common vision by improving clarity within planning activities and developing mechanisms to share responsibility. From this starting point, we adapt our survey questions to reflect the common vision concept within organizations. See questions 1-4 in appendix A.

Construct	Dimension	Authors
Common Vision	Strategic vision	Spekman, Kamauff, and Myhr, 1998
	Strategic vision	Stank, Keller, and Closs, 2001
	Strategic vision	Stank, Keller, and Closs, 2002
Organizational Learning	Learning environment, learning processes, and reinforcing leadership	Garvin, Edmondson, and Gino, 2008
Supply Chain Disruption Orientation (SCDO)	Encouraging employees to act	Bode, Wagner, Petersen, and Ellram, 2011
Routine Rigidity	Organizational rigidity	Gilbert, 2005
	Organizational inertia	Viellechner and Wulf, 2010
Information Quality	Accuracy, adequacy, completeness, reliability, and timeliness	Li, Rao, Ragu-Nathan, and Ragu-Nathan, 2005
Warning Capabilities	Identify and communicate	Craighead et al., 2007
	Early and late warning	Schmeidl and Jenkins, 1998
	Discovery	Hays and Hill, 2001
	Monitoring	Grover and Malhotra, 2003
	Communication	Chen and Paulraj, 2004
	Communication	Chen, Paulraj, and Lado, 2004
	Proactively detect, interpret, and report	Hall and Citrenbaum, 2009
	Identify/mitigate threats in advance	Zsidisin and Ritchie, 2009
Recovery Capabilities	Proactive and reactive response	Craighead et al., 2007
	Engaging responses, assets and capabilities	Olavarrieta and Ellinger, 1997
	Response agility	Schmeidl and Jenkins, 1998
	Recovery expectations and performance	McCollough, Berry, and Yadav, 2000
	Early involvement	Koufteros, Vonderembse, and Doll, 2001
	Practice recovery behaviors	de Jong and de Ruyter, 2004

Table 2- Constructs, dimensions, and originating authors.

### **Supply chain disruption orientation**

We adapt measurement items for SCDO from a study that investigates response efforts during periods of disruption (Bode et al., 2011). SCDO works as a motivating force encouraging employees to act when there is mismatch between information needs and what is available. We envision that this construct is similar to learning from mistakes and near misses, a base construct from high reliability theory. If an organization cannot overcome the cultural barrier of learning from their mistakes, then practitioners will limit their problem solving potential. See questions 5-8 in appendix A.

### **Organizational learning**

Questions pertaining to the organizational learning construct originate from Garvin, Edmondson, and Gino (2008). In this article, the authors provide a tool kit to determine “if yours is a learning organization.” We phrase questions to tap three key organizational learning dimensions: supportive learning environment, learning processes, and reinforcing leadership. See questions 9-12 in appendix A.

### **Routine rigidity**

Gilbert (2005) conceives routine rigidity along with the resource rigidity construct. Measures attempt to understand why employees are reluctant to change processes and routines when transformation is necessary. Within the literature, few questions reflecting routine rigidity are available. Therefore, we generate statements

based on Viellechner and Wulf's (2010) work as they sought to understand inertia within the airline industry. In their work, Viellechner and Wulf investigate the causal factors of routine rigidity. See questions 13-16 in appendix A.

### **Information quality**

We adapt measurement items for the information quality construct from Li et al. (2005). These researchers use five items to evaluate the quality of information shared with partners. We interpret this as external trading partners such as raw material suppliers and outside service providers. From this research, information quality dimensions include accuracy, adequacy, completeness, reliability, and timeliness. We alter the original questions to address information quality from an intra-organization perspective. See questions 17-19 in appendix A.

### **Warning capability**

We adapt the measures for warning capability from the concept of discovery (Hays and Hill, 2001) and monitoring (Grover and Malhotra, 2003) to tap the construct's identification dimension. Also, we derived questions concerning communication from Chen and Paulraj (2004) and Chen, Paulraj, and Lado (2004). The communication measurement items focus on "events or changes that may affect the other party." We adapt them to refer to the internal communication between the disaster command center and other intra-organization departments and employees. See questions 20-23 in appendix A.

## **Recovery capability**

We develop the measures for recovery capabilities based on McCollough, Berry, and Yadav's (2000) work on recovery expectations, Koufteros, Vonderembse, and Doll's (2001) work on early involvement, and de Jong and de Ruyter's (2004) work on proactive recovery behaviors. To insure that we capture both the pre-emptive and reactive dimensions of recovery, we create items that looked at pre- and post-disruption response efforts. We also add control measures pertaining to the organization's command center, to determine how these entities affect SC disruption management.

When designing warning and recovery practices, managers need to keep four overarching principles in mind. First, the organization's communication infrastructure significantly affects how practitioners communicate information internally and across the supply chain. Managers should design warning and recovery systems to insure quick communication of pertinent information to appropriate personnel. This includes methods of transmission, protocols on how to categorize and handle SC threats, and escalation procedures for unexpected threats. Second, practitioners should refine their scanning, communication, and recovery activities with real-world testing. While training and practice may be the only opportunity for rare events, actual use during a SC disruption with structured feedback is the best method to improve capabilities. Smith (2011) suggests that scenario planning and simulations are important techniques to test strategies and plans. Third, while there is no way to eliminate all false positives, managers should attempt to minimize their effect (Schmeidl and Jenkins, 1998). This requires extensive

communication and a keen understanding about disruption probabilities. Without sustained communication efforts, organizations will experience a loss of faith as false positives undermine the entire SCRM strategy. Finally, individuals involved with both warning and recovery efforts should be free of organizational inertia or the influence of the corporate culture (Smith, 2011). When biased by management or political initiatives, information about SC disruptions may degrade and slow warning and recovery efforts. See questions 24-27 in appendix A.

### **Research Methodology**

#### **Expert review**

To establish face validity of the study's definitions and measures, we reviewed concepts with several practitioners and academic experts (Anastasi, 1988). These informants validate our thinking with item-to-concept sorting procedures (Q-sorts) and qualitative feedback on measure wording and model design. During Q-sorting procedures, respondents spoke to incomplete definitions, misleading concepts, and the Qualtrics.com survey instrument. After adjusting questions based on the Q-sorts, we then asked procurement professionals to review the survey instrument. This study's primary investigator directed the interviews and asked clarifying questions. We recorded the interviews and made changes to the final survey instrument based on the experts input.

Between April and November 2012, we interviewed six procurement professionals from several industries. We asked interviewees about the hypothetical model, survey questions, and proposed hypotheses. Procurement director #1 works at in a

large medical center, procurement director #2 and #3 are employees at a large retailer. Procurement director #4 works at a medium-size university and procurement professional #5 is a supply corps officer. Additionally, we were able to interview a procurement manager from a large retailer.

### **Unit of analysis**

For this study, the unit of analysis is the strategic business unit (SBU). We postulate that while managers develop RM strategies at the organizational level that employees within the SBU shape the strategy for deployment and execution. Therefore, we collect survey data from one respondent within the SBU. In particular, procurement directors and buyers provide data about the intra-organization competencies, RM capabilities, and their perception of performance.

### **Data collection**

We collected pilot data from procurement directors at university-affiliated hospitals. Initially, we sent an email survey and a gift card incentive to 938 hospital professionals. This netted 49 useable responses or 5.2% of the sample frame. Based on the results we reduced the number of questions and amended several unclear statements.

For the full survey, we sampled 2,700 procurement professionals from multiple industries. A breakdown of the respondents is included in Figure 2. Empanelonline.com, a market research company, administered the survey and collected 358 responses. Market research panels allow researchers to control their data collection efforts, by screening and



validating panel participants (Ayyagari, Grover, and Purvis, 2011; Carter, 2012). “When used in conjunction with appropriate screening questions, these features help prevent sampling and statistical conclusion errors by ensuring that researchers have access to appropriate sample frames for their studies and can acquire adequate sample sizes and response rates” (Carter, 2012, p. 208). See appendix B for a full description of Empanelonline.com’s data collection procedures.

Command Center (COMMAND)		Annual Purchasing Spend (SPEND)	
Yes	165	< \$100,000	8
No	43	\$100,000 - \$499,999	27
		\$500,000 - \$1 Million	50
Position with the Firm (RANK)		\$1-10 Million	61
VP or above	41	\$10-25 Million	34
Director	52	\$25-99 Million	17
Manager	72	>\$100 Million	11
Senior Buyer	12		
Buyer	14	Annual Total Revenues (REVENUE)	
Analyst	8	< \$5 Million	14
Other	5	\$5-49 Million	41
		\$50-99 Million	37
Years of Experience (TENURE)		\$100-499 Million	49
< 1 Year	0	\$500-999 Million	30
1-5 Years	22	\$1-10 Billion	26
6-10 Years	69	>\$10 Billion	10
11-15 Years	48		
15-19 Years	38		
20-25 Years	19		
>25Years	9		

Figure 2: Respondent profile

Of the 358 responses, 137 respondents were not eligible to complete the survey because they could not adequately respond to the survey’s themes (less than 50 percent of respondent’s time was devoted to procurement/purchasing activities) or their organization

was too small (less than 50 employees within their organization). This left us with 221 survey responses.

### **Sample size**

Before collecting any data for this research, we calculated the sample size to ensure adequate power to detect the relationships within this study. Initially, we followed the standards set by Bartlett, Kotrlik, and Higgins (2001). Their calculations require three key inputs: alpha level ( $t$ ), estimate of standard deviation in the population ( $s$ ), and an acceptable margin of error for mean being estimated ( $d$ ). We selected an alpha level of 0.01. This conservatively accounts for the level of risk that the researcher is willing to accept. We used the standard deviation estimate suggested by Bartlett of 1.167. This conservative figure estimates the standard deviation for a 7-point scale. Lastly, we used 0.21 as the acceptable margin of error for the estimated mean. This represents the number of options within a scale multiplied by the acceptable margin of error a researcher is willing to accept.

$$n_o = \frac{(t)^2 * (s)^2}{(d)^2} = \frac{(2.576)^2 * (1.167)^2}{(7*0.03)^2} = 204.925 \text{ or approximately 205 respondents. With 206}$$

valid responses, we have exceeded the minimum suggested requirements.

### **Missing data**

We tested the original data to determine if the omitted variables are missing completely at random (MCAR). Using Little's test, we conclude the data is MCAR (Chi-

Square = 410.366, DF = 432, Sig. = 0.766). Hence, we replace any missing data using EQS version 6.1. With less than 1 percent, we follow the advice of Tabachnick and Fidell (2007) and use expectation-maximization (EM) imputation to estimate missing variables.

### **Preliminary analysis**

We screened the data to identify unusual responses, which resulted in the rejection of thirteen (13) responses (eight were excluded due to “straightlining,” two were excluded for unusually short response time (less than 40 seconds), and three were excluded because the majority of the questions were unanswered. Then, using Mahalanobis distance values to evaluate multivariate outliers, we removed two responses. Using EQS 6.1, we confirmed that the degree of multivariate skewness (Mardia, 1970) was also excessive. A normalized Mardia’s estimate of 52.07 indicates positive and significant multivariate kurtosis. When we removed two (2) outliers, and the Mardia estimate dropped to 47.36. We conducted a preliminary analysis on the remaining data, including tests for outliers and kurtosis (Tabachnick and Fidell, 2007). The final sample resulted in 206 responses or 12.98 percent of the potential respondent pool.

Even with two outliers removed, we consider the data non-normal. Therefore, we use the robust estimates available in EQS 6.1. This method allows users to analyze non-normally distributed data with covariance based SEM techniques. Robust methods use Satorra-Bentler

Chi-square estimates (Satorra and Bentler 1988). In addition, we provide standard errors, CFI, and RMSEA from SEM output based on Bentler's (1995) calculations. Byrne (2006) insists the robust methodology is valid, even though the data violates the normality assumption. Chou, Bentler, and Satorra, 1991) have confirmed, via simulation, that robust methods yield accurate estimates.

### **Common method bias**

Podsakoff, McKenzie, and Podsakoff (2012) refer to common method bias (CMB) when describing the systematic variance introduced into research by the measurement method. Researchers should address this phenomenon as it can affect the relationship between constructs. In particular, CMB can distort construct reliability estimates (Bagozzi 1984) and the relationship parameter estimates (Podsakoff et al. 2012)

Researchers should attend to the CMB phenomenon during measurement design. When done proactively, investigators are able to lessen the influence of the measurement method. Initially, we employ multiple rounds of Q-sorting and pretesting to eliminate wording ambiguity associated with specific questions. Procedurally, we changed the anchors within the survey instrument in order to eliminate common scale properties (Podsakoff et al., 2012).

Further, as suggested by Podsakoff et al. (2012), we also tested the measurement instrument statistically. We employed both the latent factor and marker variable test to identify method bias. (See Appendix C for full results.) Using the method factor test, we identified four items, organizational learning1, warning capability-1, information quality-

1, and SCDO1, indicating potential bias. For each item, the method factor accounted for 21.2 percent, 31.1 percent, 28.9 percent, and 32.9 percent of the total variance, respectively. We further assess these findings by comparing the S-B  $X^2$  of the original model as compared to the model where the method factor was included (Byrne 2006). We found the change in S-B  $X^2$  to be significant at  $p < 0.001$ . This indicates that additional common variance was accounted for, when the method factor was included.

The marker variable test showed similar results. In this case, we compare the average variance extracted (AVE) of the original model to the AVE of the model where the marker variable is included. In total, the AVE decreased from 0.677 (original model) to 0.594 (model with marker variable). Thus, both the method factor and marker variable test indicate that common method bias is present within our data set. We, therefore, take the conservative approach and control for the method bias in subsequent analyses.

### **Non-response bias**

Non-response bias occurs when respondents that failed to answer a survey provide significantly different answers than respondents that did complete a survey. Applying the logic of Armstrong and Overton (1977), we compare early and late responders. For this, we compare the means for three control variables: years of work experience (WORK), annual revenue spent (SPEND), and annual revenue (REVENUE). Table 3 below indicates that we did not find discernible differences between early and late respondents. We conclude that non-response bias is not a significant problem.

<b>Tests of Non-Response Bias</b>				
Work Experience (WORK)	Mean	Std. Dev.	t-stat	p-value (2-tail)
Early Respondents (N=15)	3.47	1.06	0.31	0.76
Late Respondents (N=15)	3.87	1.06		
Annual Spend (SPD)	Mean	Std. Dev.	t-stat	p-value (2-tail)
Early Respondents (N=15)	3.6	0.99	0.53	0.6
Late Respondents (N=15)	3.27	1.75		
Annual Revenue (REV)	Mean	Std. Dev.	t-stat	p-value (2-tail)
Early Respondents (N=15)	3.87	0.92	0.24	0.81
Late Respondents (N=15)	3.27	1.71		

Table 3: Tests of Non-Response Bias

### Confirmatory factor analysis

Using Menor and Roth's (2007) methodology, we employ confirmatory factor analysis (CFA) to assess the unidimensionality, reliability and validity (convergent and discriminant) of the proposed measures. Table 4 illustrates the unidimensionality and reliability of the proposed measures. Given that the  $X^2$  statistic was significant, we follow MacCallum's (1990) advice and evaluate the absolute and incremental fit indices. Using EQS version 6.1, we calculate and report several fit measures in Table 4. We compared the CFI to the generally accepted guideline value of 0.90. In addition, all of the SRMRs were below the best practice standard of 0.08. We also report RMSEA values for each construct and note that several are above 0.08, which suggests mediocre fit (MacCallum, Browne, & Sugawara, 1996). Recently, Kenny, Kaniskan, & McCoach, (2011) suggested

that RMSEA values should not be computed for low degree of freedom models, as they found the incremental fit calculation overinflated the resulting RMSEA values.

Item	# of items	CFI	RMSEA	SRMR	Cronbach's Alpha	Composite reliability	Average variance extracted
Common Vision	4	0.956	0.148	0.035	0.878	0.88	0.695
Organizational Learning	4	0.988	0.071	0.025	0.885	0.886	0.705
DSRC	8	0.924	0.108	0.052	0.927	0.928	0.671
Routine Rigidity	4	0.925	0.243	0.07	0.847	0.855	0.657
SCDO	4	1.00	0	0.01	0.847	0.855	0.657
Information Quality	3	1.00	0	0	0.874	0.888	0.757
Warning Capability	4	0.945	0.179	0.062	0.881	0.878	0.693
Recovery Capability	4	0.986	0.090	0.023	0.855	0.862	0.667

Table 4: Unidimensionality and reliability of warning and recovery capabilities

To evaluate the measure's reliability, we use the CFA standardized factor loadings to calculate composite reliability and average variance extracted (AVE) values. In this context, "reliability refers to the extent to which the questionnaire is free from measurement error" (Baroudi and Orlikowski, 1987, p. 10). Bagozzi and Yi (1988) suggest that researchers compare the calculated composite reliability values to a standard of 0.70. All measures, including those for warning and recovery capability, exceed this guideline. With over 70% of the variance estimating the true score variance, the evidence indicates that the measures reliably reflect the constructs of interest. Further, we compare the AVE to the best practice value of 0.50 (See Table 5). We surmise that the measures account for the constructs variance rather the error. Both the AVE and the composite reliability figures suggest that the measures accurately reflect the proposed constructs.

Items	Common Vision	Supply Chain							AVE
		Disruption Orientation	Org Learning	Routine Rigidity	Information Quality	Warning Capability	Recovery Capability	Performance	
Common Vision-1	0.726								0.695
Common Vision-2	0.801								
Common Vision-3	0.797								
Common Vision-4	0.761								
SCD0-1		0.68							0.645
SCD0-2		0.649							
SCD0-3		0.737							
SCD0-4		0.674							
Organizational Learning-1			0.637						0.705
Organizational Learning-2			0.813						
Organizational Learning-3			0.766						
Organizational Learning-4			0.794						
Routine Rigidity-1				0.729					0.657
Routine Rigidity-2				0.688					
Routine Rigidity-3				0.887					
Routine Rigidity-4				0.784					
Information Quality-1					0.767				0.757
Information Quality-2					0.757				
Information Quality-3					0.792				
Warning Capability-1						0.645			0.693
Warning Capability-2						0.689			
Warning Capability-3						0.857			
Warning Capability-4						0.9			
Recovery Capability-1							0.729		0.667
Recovery Capability-2							0.729		
Recovery Capability-3							0.722		
Recovery Capability-4							0.71		
Performance-1								0.626	0.634
Performance-2								0.76	
Performance-3								0.764	

Table 5: Measurement properties of reflective constructs



We evaluate the convergent validity by inspecting the magnitude and sign of the standardized loading factors (see Table 6). All loadings factors appear to be directionally appropriate (concurrent validity). In addition, the average variance extracted (AVE) for each construct is exceeds > 0.50 the suggested guidelines found within literature (Fornell & Larcker, 1981). This inspection suggests the proposed measures exhibit convergent validity.

Items	Composite Reliability	AVE	#of items	Items	Common Vision	Organizational Learning	Warning Capability	Recovery Capability	Routine Rigidity	SCDO	Information Quality	Performance
Common Vision	0.880	0.695	4	CV	0.83	30.31	1.66	36.64	43.93	42.41	37.99	20.31
Organizational Learning	0.886	0.705	4	OL	0.87	0.84	32.06	38.41	39.14	38.17	27.16	21.36
Warning Capability	0.878	0.693	4	WC	0.76	0.70	0.83	9.16	61.01	34.95	26.21	36.85
Recovery Capability	0.862	0.667	4	RC	0.81	0.82	0.92	0.82	40.82	28.68	48.98	16.4
Routine Rigidity	0.855	0.657	4	RR	(0.01)	(0.17)	0.09	0.01	0.81	46.08	30.78	54.27
SCDO	0.846	0.645	4	SCDO	0.73	0.68	0.72	0.70	0.05	0.80	47.71	38.26
Information Quality	0.888	0.757	3	IQ	0.74	0.59	0.77	0.78	0.10	0.78	0.87	35.79
Performance	0.795	0.634	3	PERF	0.84	0.84	0.75	0.85	0.09	0.69	0.76	0.80

Table 6: Correlations<sup>1</sup> square root of average variance extracted (AVE)<sup>2</sup> and chi-square differences<sup>3</sup> ()<sup>4</sup>

1. Correlations bottom left triangle
2. Square root of average variance extracted (AVE) on diagonal. This converts the AVE to the standard deviation scale, so it can be compared to correlations located in bottom left triangle.
3. Satorra-Bentler differences top right triangle (SBDIFF.exe)
4. Negative correlations between factors

Finally, we explore the scale's discriminant validity. We assess the multi-items scales by estimating 42 models (21 constrained and 21 unconstrained) and calculating the  $X^2$  difference for nested models (Satorra and Bentler, 2001) (See Appendix E for input and output variables). Since our data set is non-normal, we use the scaled Satorra-Bentler chi-square values (S-B) within the EQS 6.2 software. We calculate the S-B  $X^2$  differences using the scaled difference procedure prescribed by Bryant and Satorra (2012). The S-B  $X^2$  difference tests were executed between the constrained model (correlations between factor pairs constrained to one (1)) and the unconstrained model (correlations between factor pairs are allowed to correlate freely). We also produced a third set of models to estimate the scaling correction factor. Bryant and Satorra (2012) provide this correction to accurately calculate the S-B  $X^2$  differences.

When comparing factor pairs, we expect significant differences between constrained and unconstrained models. Two relationships do not show significant differences at the  $P < 0.001$  value, hence they are not unique constructs (common vision - warning capability and warning capability - recovery capability). Particularly concerning is the lack of difference (S-B  $X^2$  difference of 9.16) between the warning capability and recovery capability constructs. This indicates that the two constructs are not significantly different. We further confirm this finding by evaluating the correlation between the warning capability and recovery capability constructs. At 0.917, the evidence suggests these are not unique measures. Therefore, we cannot conclusively establish discriminant validity between the warning capability and recovery capability constructs.

### **Alternate Model**

As the warning and recovery capability constructs are not unique, that is due to a lack of discriminant validity, we offer an alternate model (Figure 3). In the new representation, warning and recovery represent two dimensions of an organization's *disruption sensing and response capability*. The warning dimension speaks to the organization's ability to scan the SC for anomalies and then to communicate information about threats to partners. The recovery dimension addresses an organization's response capabilities. Specifically, they call attention to preemptive recovery, which takes place before an actual disruption occurs, and reactive recovery for response initiatives that occur after a SC disruption has manifest. Taken together, disruption sensing and response capability reflects a multi-dimensional construct of how an organization addresses SC disruption

As in the first model, the alternate model also has the same four antecedent competencies, one mediating variable, information quality, one capability level construct representing disruption sensing and response capability, and organizational performance. Specifically, the four competencies, common vision, SCDO, organizational learning, and routine rigidity, reflect an organization's orientation. Disruption sensing and response capability is representative of the organizational RM capabilities. Information quality mediates the relationships between the intra-organization competencies (common vision, SCDO, organizational learning, and routine rigidity) and the organizational RM

capabilities. The performance construct represents the practitioners' perception of financial and operational performance.

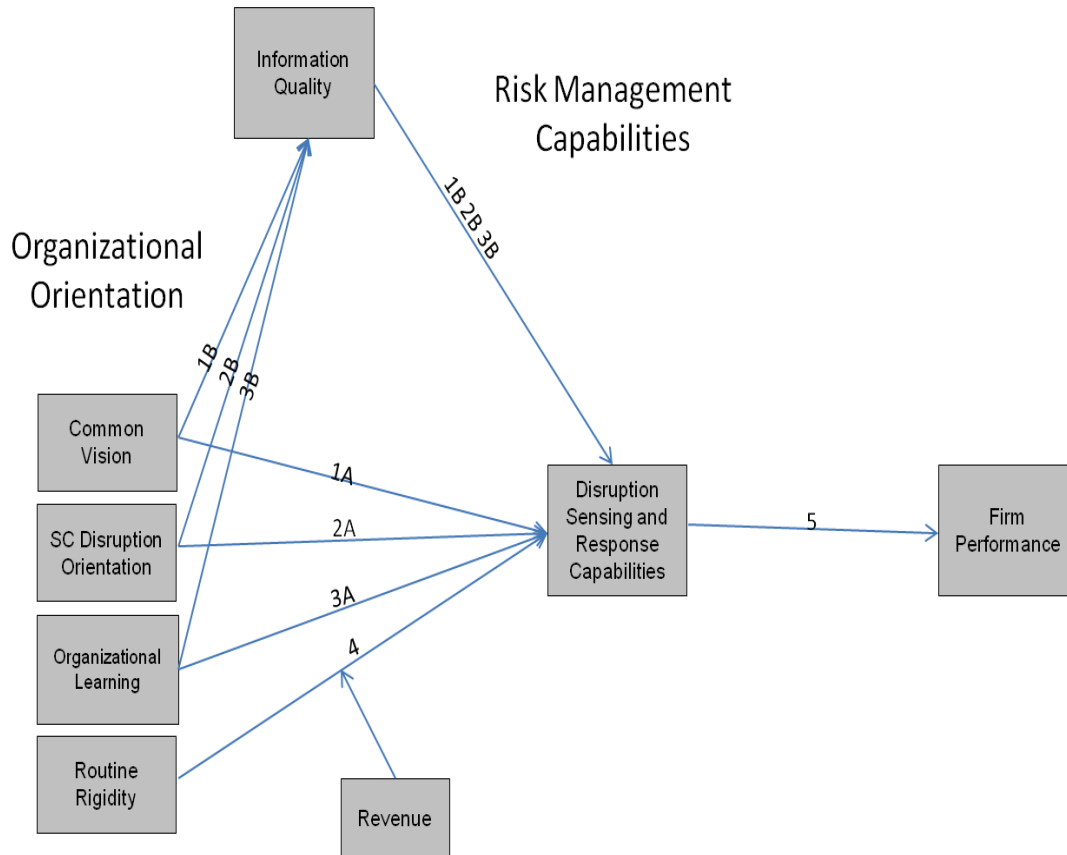


Figure 3- Alternate Model

### Relationship between common vision and disruption sensing and response capability (H1A)

As noted above, executives use a common vision to provide insight on how to manage an organization. The messages should highlight key objectives and show how

attaining goals aligns with an employee's belief system. When managers properly communicate the common vision, practitioners are motivated to pursue the organization's objectives without direct incentives.

When considering the relationship between the common vision competency and disruption sensing and response capability, executives should outline why scanning, communicating, and responding to SC disruptions is paramount. This includes written and verbal communications about how managing SC risk is good operationally and financially. We avow that addressing SC disruption within the common vision allows practitioners to understand how RM leads to better service, balanced operations, and steady shareholder value (Hendricks and Singhal, 2003, 2009).

We suppose that highly reliable organizations seek a more balanced approach emphasizing long-term safety, improvisation, and redundancy, along with cost management (for non-profits) or profits (for profit organizations). Further, we believe that executives must clearly communicate the common vision messages to employees if they are to develop a reliable organization. From this position, when organizations properly develop the common vision competency, we believe they will have improved scanning, communication, and response abilities. Thus, we propose the following hypothesis:

*H1A-Organizations with higher common vision levels of will have higher disruption sensing and response capability levels.*

**The mediating affects of information quality on the relationship between common vision and disruption sensing and response capability (H1B)**

As executives communicate their vision to employees, they need to insure the information quality of the messages. Without high information quality, employees may misunderstand the intent and fail to link key objectives to personal beliefs. While information quality has been researched as a mediator (e.g. Pearson, Tadisina and Griffin, 2012 or McDowell and Karriker, 2009), its affect on abstract communications such as a common vision is absent within literature. Therefore, we advise that information quality mediates the relationship between common vision and the disruption sensing and response capability construct.

From a high reliability perspective, employees need a foundation from which to act. Executives need to outline, within the common vision, the organization's goals as they pertain to SC disruption. When done, executives empower employees to respond quickly and without fear. Ultimately, when quality common vision messages flow throughout an organization, we envision that they help reduce confusion and frustration, which enhances organizational success (Huber and Daft, 1987). Thus:

*H1B-Information quality mediates the relationship between common vision and disruption sensing and response capability*

## **Relationship between supply chain disruption orientation and disruption sensing and response capabilities (H2A)**

Managers should establish a *supply chain disruption orientation* (SCDO) to ensure that practitioners have a concern for and the motivation to act upon SC disruptions (Bode et al., 2011). While stemming from management's communication, SCDO is an operations level posture that affects the culture of an organization. Thus, employees are encouraged to think about and seek out behaviors that are disruptive. When viewed with an high reliability theory lens, a SCDO is similar to situational awareness. Situational awareness refers to an employee's perception of their environment, which helps comprehend the current situation, and envision future states (Endsley, 1995; Weick et al., 1999)

We imagine that a SCDO should complement an organization's disruption sensing and response capability by motivating practitioners to seek out and respond to various SC threats. For the warning dimension, we embrace Daft and Weick's (1984) view that organizations can develop competencies to scan their environment, interpret, and then act upon various phenomena. When employees understand that uncertainty is present, they can tune scanning systems to seek out anomalies.

For the disruption sensing and response capability recovery dimension, a SCDO motivates an organization towards SC stability using its recovery capabilities. (Bode et al., 2011). With this posture, organizations develop abilities to withstand SC disruptions. When experienced, employees interpret, adapt, and quickly overcome manifest consequences. Thus:

*H2A-Organizations with higher SCDO levels will have higher disruption sensing and response capability levels.*

**The mediating affects of information quality on the relationship between SCDO and disruption management capabilities (H2B)**

Messages outlining a SCDO provide guidance to operators on how to perform both before and after a SC disruption. Executives should construct these communications with high information quality, so practitioners understand and embrace the messages. Otherwise, operators may not be motivated to seek out potential threats and quickly respond to actual disruptions.

From a high reliability theory perspective, SCDO is analogous to mindfulness, where practitioners are preoccupied with failure, sensitive to operations, and committed to resilience. If managers fail to outline the organization's SC goals, then practitioners may hesitate and delay actions that either mitigate disruption consequences and/or return the SC to normal. Further, the information quality of these messages must be paramount, as confusion may drive practitioners to sub-optimal solutions.

The existing literature suggests that organizations can enhance performance when managers improve the information quality of organizational processes (Preuss, 2003). We postulate that this is true within SC networks where practitioners gather information from multiples sources and make time sensitive decisions. Hence, we offer the following hypothesis:



*H2B-Information quality mediates the relationship between SCDO and disruption sensing and response capability*

### **Relationship between organizational learning and disruption sensing and response capability (H3A)**

Organizational learning reflects an organization's ability to extract information about a phenomenon, digest it, and alter future behavior. In high reliability theory vernacular, organizations learn from experimentation (Rochlin, 1993), trial-and-error (LaPorte and Consolini, 1991), and adaptive learning (Weick et al., 1999). We argue that organizations with high levels of organizational learning competency will have improved disruption sensing and response capability levels.

We envision that organizations use experimentation and trial-and-error to develop the warning dimension of the disruption sensing and response capability construct. Even with routine activities, experimentation and trial-and-error allows practitioners to develop their warning tactics as outcomes change over time. This is particularly true as managers' experiment with different SC configurations, changing linkages and relationships as needs change.

Additionally, we liken adaptive learning abilities to response practices used to restore the SC to normalcy. As disruptions occur, SC practitioners should address the disruption with mitigation and response tactics. Adaptive learning allows the organization to learn on the fly and adjust, as the situation requires.

Further, as an organization develops its reliability capabilities, it should expect a reduction in the number of disruptions. Therefore, highly reliable organizations should develop a preoccupation with failure, where practitioners recognize “that all of the potential failure modes into which the highly complex technical systems could resolve themselves have yet to be experienced” (Schulman, 1993, p. 364). Thus, we imagine that managers can develop organizational learning abilities as a means to improve the warning and recovery abilities, which develops an organization’s disruption management capabilities. Thus:

*H3A-Organizations with higher organizational learning levels will have higher disruption sensing and response capability levels.*

**The mediating affects of information quality on the relationship between organizational learning and disruption sensing and response capability (H3B)**

Organizations use organizational learning techniques to enhance understanding (Damanpour, 1991), influence behavior (Huber, 1991), improve problem solving (Senge, 1990), and boost overall performance (Matsuno and Mentzer, 2000; Hult, Ferrell, and Hurley, 2002). Practitioners can then use the knowledge acquired from these processes to develop improved disruption scanning and response systems. However, in order to benefit from organizational learning initiatives, organizations must be able to gather high quality data from different information systems and partners. When high information quality material is available, organizational learning practices enhance organizational processes and shorten the time associated with learning a new process. If information

quality is low, then practitioners and the organization will struggle to learn as information becomes available. Thus:

*H3B-Information quality mediates the relationship between organizational learning and disruption sensing and response capability.*

#### **Relationship between routine rigidity and disruption sensing and response capability (H4)**

The extant literature suggests that employees are subject to routine rigidity when embedded processes are hard to amend (Teece et al. 1997). As this construct was born from the organizational inertia literature, the strength of routine rigidity grows as an organization's size increases. This occurs as employees become accustomed to a particular response, especially during uncertain periods. Tushman and O'Reilly (1996) indicate that overcoming routine rigidity is difficult, because employees perceive cultural pressure.

Previous research also suggests that certain organization types can overcome routine rigidity. Bala and Venkatesh (2007), for example, found that nondominant firms (compared to dominant firms) experienced less routine rigidity, because the routines used depended on the partner's relationship type. Stated differently, employees changed processes when dealing with different partners. They also found that non-adaptive organizations were unable to overcome routine rigidity (Bala and Venkatesh, 2007).

We speculate that in uncertain times, employees will embrace routine rigidity and diminish the disruption sensing and response capability levels within an organization. Specifically, we purpose that larger organizations will experience higher levels of routine rigidity as social inertia inhibits experimentation. Conversely, smaller organizations, adept to adaptation, should experience less routine rigidity as employees are used to adaptation. From this rationale, we hypothesize that routine rigidity negatively affects disruption sensing and response capability. However, due to the inertia effect on the routine rigidity construct, we propose a moderated effect that varies depending on organization size. Similar to previous research, we use annual revenue as a proxy for organizational size (Bajwa, Lewis, Pervan and Lai, 2005). Hence, we offer the following hypothesis:

*H4-Organizations with higher routine rigidity levels will have lower – disruption sensing and response capability levels.*

#### **Relationship between disruption sensing and response capabilities and organizational performance (H5)**

When decomposing the disruption sensing and response capability construct, we find that organizations should develop abilities to scan the SC horizon, communicate information about threats, and make possible both preemptive and reactive response tactics. Leveraging the high reliability perspective, this suggests that by developing certain RM practices that organizations can mitigate SC threats and minimize the impact of actual SC disruptions. However, in order to manage these competing goals, highly

reliable organizations as are preoccupied with failure, sensitive to operations, and committed to resilience. We put forward that by doing so, an organization can also improve its level of performance. Hence, we offer the following:

*H5-Organizations with higher disruption sensing and response capability levels will have higher levels of performance.*

We summarize the proposed hypotheses in Table 7 and discuss the control variables in section 5.3. Then, we describe the CFA methodology for operationalizing the disruption sensing and response capability construct and conducting tests of the hypotheses

Item	Hypothesis
H1A	Organizaitons with higher common vision levels of will have higher disruption sensing & response capability levels
H1B	Information quality mediates the relationship between common vision and disruption sensing & response capability levels
H2A	Organizaitons with higher SCDO levels will have higher disruption sensing & response capability levels
H2B	Information quality mediates the relationship between SCDO and disruption sensing & response capability levels
H3A	Organizaitons with higher organizational learning levels will have higher disruption sensing & response capability levels
H3B	Information quality mediates the relationship between organizational learning and disruption sensing & response capability levels
H4	Organizations with higher routine rigidity levels will have lower disruption sensing & response capability levels
H5	Organizations with higher disruption sensing & response capability levels will have higher levels of performance

Table 7: Summary of Hypotheses- alternate model

### Control variables

We include four control variables in this research: command center (COMMAND), organization rank (RANK), years in position (TENURE), and annual purchasing spend (SPEND). Participants involved in the exploratory interviews spoke regularly about the activation of a COMMAND during SC disruptions. A command center allows organizations to respond to SC disruptions in a centralized manner. Within a command center environment, we believe that managers can allocate resources and make decisions because more and higher quality information is available. We also believe it important to control for RANK and TENURE as it should affect understanding of SC disruptions. Previous research suggests that experience affects a practitioner's

behaviors and decision making (Daft and Weick, 1984; Roberts, 1990; Bode et al., 2011). By extension, we assume that higher ranked and tenured practitioners will have more experience with SC disruptions and the tools to manage them. Finally, SPEND is included as a proxy for organizational size.

### **Confirmatory factor analysis for alternate model**

With the CFA analysis, we assess the unidimensionality, reliability, convergent validity and discriminant validity of the proposed measures. See Table 8 for a summary of findings Table 9 for specific item measurement properties. We assess the scale's unidimensionality by creating models for each measure. Using the CFI as an indicator of fit, we find that all CFIs are greater than the generally accepted cut-off value of 0.90. In addition, SRMR values fall below the 0.08 standard. We also report RMSEA values for each construct and note that several are above 0.08, which suggests mediocre fit (MacCallum, Browne, & Sugawara, 1996). Recently, Kenny, Kaniskan, & McCoach, (2011) suggested that RMSEA values should not be computed for low degree of freedom (df) models, as they found the incremental fit calculation overinflated the resulting RMSEA value. Therefore, the results indicate that all items loaded appropriately.

Item	# of items	CFI	RMSEA	SRMR	Cronbach's Alpha	Composite reliability	Average variance extracted
Common Vision	4	0.956	0.148	0.035	0.878	0.88	0.695
Organizational Learning	4	0.988	0.071	0.025	0.885	0.886	0.705
DSRC	8	0.924	0.108	0.052	0.927	0.928	0.671
Routine Rigidity	4	0.925	0.243	0.07	0.847	0.855	0.657
SCDO	4	1.00	0	0.01	0.847	0.855	0.657
Information Quality	3	1.00	0	0	0.874	0.888	0.757

Table 8- Unidimensionality and reliability of measures including disruption sensing and response capability



Items	Common Vision	Supply Chain Disruption Orientation	Org Learning	Routine Rigidity	Information Quality	Disruption Sensing and Response Capability	Performance	AVE
Common Vision-1	0.741							0.695
Common Vision-2	0.81							
Common Vision-3	0.799							
Common Vision-4	0.762							
SCD0-1		0.697						0.645
SCD0-2		0.675						
SCD0-3		0.742						
SCD0-4		0.679						
Organizational Learning-1			0.623					0.705
Organizational Learning-2			0.802					
Organizational Learning-3			0.755					
Organizational Learning-4			0.785					
Routine Rigidity-1				0.741				0.657
Routine Rigidity-2				0.702				
Routine Rigidity-3				0.882				
Routine Rigidity-4				0.775				
Information Quality-1					0.79			0.757
Information Quality-2					0.766			
Information Quality-3					0.799			
Disruption Sensing & Response Capability- 1						0.664		0.671
Disruption Sensing & Response Capability- 2						0.723		
Disruption Sensing & Response Capability- 3						0.831		
Disruption Sensing & Response Capability- 4						0.864		
Disruption Sensing & Response Capability- 5						0.705		
Disruption Sensing & Response Capability- 6						0.691		
Disruption Sensing & Response Capability- 7						0.705		
Disruption Sensing & Response Capability- 8						0.743		
Performance-1							0.649	0.634
Performance-2							0.781	
Performance-3							0.744	

Table 9: Measurement properties of reflective constructs

We evaluate the measures' reliability, using the standardized factor loadings provided in the CFA analysis. This method allows us to calculate values for composite reliability and the AVE. We compare the measures composite reliability values to a standard of 0.70 as discussed by Bagozzi and Yi (1988). All measures, including the newly operationalized disruption sensing and response capability, range from 0.855 to 0.928. Hence, the composite reliability values indicate the measures reliably represent the theoretical constructs. Further, we calculate AVE values for each measure and compare them to the established cut off value of 0.50. Thus, we are satisfied that the measures explain the construct's variance, rather than error.

Thirdly, we assess the measures for convergent validity. To do so, we inspect the standardized loading factors to see if they are appropriate (both sign and magnitude). See Table 10 for a summary of correlations, square root of AVEs, and S-B differences. We found the factor loadings were significantly and directionally appropriate.

Items	Common Vision	Organizational Learning	Disruption Sensing & Response Capability	Routine Rigidity	SCDO	Information Quality	Performance
Common	0.83	21.43	56.99	53.7	48.23	40.62	21.29
Organizational Learning	0.88	0.84	36.67	43.48	29.33	21.07	17.15
Disruption Sensing & Response Capability	0.81	0.77	0.82	65.63	44.59	36.11	27.93
Routine	0.00	(0.15)	0.08	0.81	39.07	34.81	54.00
SCDO	0.74	0.68	0.74	0.07	0.80	46.39	44.25
Information Quality	0.74	0.58	0.80	0.13	0.79	0.85	31.92
Performance	0.83	0.83	0.81	0.11	0.68	0.75	0.94

Table 10: Correlations<sup>1</sup> square root of average variance extracted (AVE)<sup>2</sup> and chi-square differences<sup>3</sup> ()<sup>4</sup>

1. Correlations bottom left triangle
2. Square root of average variance extracted (AVE) on diagonal. This converts the AVE to the standard deviation scale, so it can be compared to correlations located in bottom left triangle.
3. Satorra-Bentler differences top right triangle (SBDIFF.exe)
4. Negative correlations between factors

Finally, we assess the discriminant validity of each measure. We used the S-B  $X^2$  difference test for nested models as our data was non-normal (Satorra and Bentler, 2001). This consists of testing 15 pairs of nested models (15 unconstrained and 15 constrained). We used Crawford and Henry (2003) SBDIFF.exe to calculate the S-B  $X^2$  differences. The results indicate that each measure demonstrates discriminant validity. This leads us to believe that the measures accurately reflect our research constructs.

### **Analysis and Findings**

We provide the minimums, maximums, means, and standard deviations for all measures in Table 11. Please note that after the imputation process we adjusted two responses to 7.0, which was the maximum of our Likert scale.

Code	Question	Minimum	Maximum	Mean	Std Dev
Common Vision-1	The management team has clearly explained our organization's vision.	2.00	7.00	5.83	1.21
Common Vision-2	Most employees are aware of my organization's primary business goals and objectives.	1.00	7.00	5.72	1.25
Common Vision-3	Most employees value my organization's goals and objectives.	2.00	7.00	5.79	1.13
Common Vision-4	When setting goals, most employees consider the organization's vision.	1.00	7.00	5.71	1.09
Org Learning-4	Within my organization, learning is key to improvement.	1.00	7.00	5.96	1.05
Org Learning-5	As an organization, we learn from our experiences.	1.00	7.00	5.94	1.11
Org Learning-6	Our ability to learn is the key to improving my organization.	3.00	7.00	6.02	1.04
Org Learning-7	As an organization we learn from our successes.	3.00	7.00	5.94	1.06
Performance-1	My organization is able to keep operating costs to a minimum.	1.00	7.00	5.52	1.22
Performance-2	My organization is able to keep out of stocks to a minimum.	1.00	7.00	5.59	1.15
Performance-3	My organization is able to keep service quality high.	1.00	7.00	5.96	1.15
DSR-1	My organization has procedures to identify threats.	1.00	7.00	5.73	1.22
DSR-2	Within my organization, there are systems to warn employees about potential threats.	1.00	7.00	5.74	1.14
DSR-3	Within my organization, the command center identifies actual disruptions.	1.00	7.00	5.73	1.20
DSR-4	The command center identifies potential threats.	1.00	7.00	5.71	1.18
DSR-5	When a disruption occurs, my organization immediately starts recovery efforts.	2.00	7.00	5.91	1.05
DSR-6	Once a threat is identified, my organization deploys resources to reduce the negative effects.	2.00	7.00	5.91	1.07
DSR-7	My organization's command center deploys recovery resources to reduce the effects of a disruption.	2.00	7.00	5.86	1.13
DSR-8	Resources can be deployed before an actual disruption occurs.	1.00	7.00	5.74	1.19
Info Qual-1	Within my organization, information used for analysis and reporting is reliable.	1.00	7.00	5.77	1.24
Info Qual-2	Within my organization, information used for analysis and reporting is timely.	2.00	7.00	5.81	1.02
Info Qual-3	Within my organization, information used for analysis and reporting is accurate.	1.00	7.00	5.84	1.06
Routine Rigidity-1	There is resistance within my organization when trying to change existing business processes.	1.00	7.00	5.05	1.67
Routine Rigidity-2	Within my organization, there are many overlapping processes.	1.00	7.00	5.13	1.48
Routine Rigidity-3	I have a tendency to resist changing how I am used to doing things within my organization.	1.00	7.00	4.72	1.91
Routine Rigidity-4	I find it difficult to learn new processes.	1.00	7.00	3.93	2.14
SCDO-1	Understanding how supply chain disruptions occur is important to my organization.	1.00	7.00	5.93	1.20
SCDO-2	As an organization, we regularly think about supply chain disruptions.	2.00	7.00	5.77	1.13
SCDO-3	We think about how supply chain disruptions can be avoided across the organization.	2.00	7.00	5.89	1.04
SCDO-4	Supply chain disruptions show my organization where we can improve.	2.00	7.00	5.86	1.05
COMMAND	Does your organization have an emergency command / center or disaster response center?	1.00	2.00	1.21	0.41
RANK	Position within the firm?	1.00	7.00	2.75	1.43
TENURE	Years / of professional work experience?	2.00	7.00	3.94	1.31
SPEND	Annual purchasing spend (approximate).	1.00	7.00	3.89	1.42
REVENUE	Annual revenues (approximate).	1.00	7.00	3.76	1.60

Table 11: Descriptive Statistics for Alternative Model

We then evaluate the model's overall fit. Because the data is non-normal, we utilize the robust fit indices:  $\chi^2 = 746.25$ ,  $df = 500$ ,  $NNFI = 0.910$ ,  $CFI = 0.924$ , and  $RMSEA = 0.049$ . Robust (maximum likelihood) statistics are appropriate when data exhibits non-normality. The structural model (i.e., the combined measurement and path model) indicates the data fits well. Existing literature shows that OM researchers use robust fit indices (Vickery, Droge, Stank, Goldsby, & Markland, 2004; Kroes & Ghosh, 2010). Consistent with these works, we report the standardized Betas, S-B  $\chi^2$  statistic, and corresponding fit indices in Table 12.

Hypothesis	Path	Unstandardized b (Std Error)	Standardized $\beta$	Confirmed
H1A	Common Vision >> Disruption Sensing & Response Capability (Direct)	0.125 (0.208)	0.131	No
H1B	Common Vision >> Info Quality >> Disruption Sensing & Response Capability (Mediated)	0.286 (0.145)	0.299	Yes
H2A	Supply Chain Disruption Orientation >> Disruption Sensing & Response Capability (Direct)	-0.051 (0.145)	-0.053	No
H2B	Supply Chain Disruption Orientation >> Info Quality >> Disruption Sensing & Response Capability (Mediated)	0.250 (0.110)	0.262	Yes
H3A	Organizational Learning >> Disruption Sensing & Response Capability (Direct)	0.436 (0.190)	0.456	Yes
H3B	Organizational Learning >> Info Quality >> Disruption Sensing & Response Capability (Mediated)	-0.167 (0.109)	-0.174	No
H4	Routine Rigidity >> Disruption Sensing & Response Capability (Direct)	0.109 (0.049)	0.114	Yes
H4	Routine Rigidity * REVENUE >> Disruption Sensing & Response Capability (Moderated)	-0.105 (0.044)	-0.110	Yes
H5	Disruption Sensing & Response Capability >> Organizational Performance	0.829 (0.085)	0.860	Yes
Control	REV= Annual Revenues >> Organizational Performance	0.038 (0.023)	0.064	No
Fit	Index	Alternate Model		
	S-B Scaled Chi-Square	746.25		
	DEGREES OF FREEDOM	500		
	COMPARATIVE FIT INDEX (CFI)	0.924		
	NON-NORMED FIT INDEX (NNFI)	0.91		
	ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)	0.049		
	90% CONFIDENCE INTERVAL OF RMSEA	(0.041, 0.056)		

Table 12: Coefficients and Robust Fit Indices for the Alternate Model

### Common vision (H1A-B)

The evidence indicates the direct path (H1A) from common vision to disruption sensing and response capability is not significant, ( $\beta = 0.125$ ,  $p=0.5488$ ). However, we

find the indirect path (H1B) from common vision to disruption sensing and response capability is significant. Upon inspection, we find that information quality fully mediates the relationships. Common vision to information quality ( $\beta = 0.560$ ,  $p = 0.0106$ ) and information quality to disruption sensing and response capability ( $\beta = 0.511$ ,  $p = 0.0051$ ) are both significant. Therefore, the resultant indirect effect equals  $\beta = 0.2862$ . Selig and Preacher (2008) suggest assessing the indirect effects with a Monte Carlo or bootstrap test that estimates the confidence interval for the indirect effect. To confirm a significant mediated effect between common vision and disruption sensing and response capability, we conduct a bootstrap analysis to determine if the confidence interval includes zero (Selig and Preacher, 2008). Based on 20,000 bootstrap samples, the 95% confidence interval (CI) ranged from 0.03994 (lower CI) to 0.6363 (upper CI) (see appendix #D for distribution of indirect effects). This confirms that the fully mediated relationship is significant. We interpret this finding in the following manner. When executives communicate the high-level objectives, they should carefully craft the common vision messages. This follows Redman's (1998) assertion that poor information quality can undermine an employee's trust, demoralize the organization, and make strategic alignment difficult.

### **Supply chain disruption orientation (H2A-B)**

The path coefficient from SCDO to disruption sensing and response capability (H2A) is not significant, ( $\beta = -0.051$ ,  $p = 0.7265$ ). However, we find a fully mediated relationship between SCDO to disruption sensing and response capability (H2B).

Specifically, information quality fully mediates the linkage between the constructs. SCDO to information quality ( $\beta = 0.489$ ,  $p = 0.0005$ ) and information quality to disruption sensing and response capability ( $\beta=0.511$ ,  $p=0.0051$ ) for an indirect total of  $\beta = 0.2410$ . Leveraging best practice, we conduct a bootstrap analysis to verify the significant mediated effect between SCDO and disruption sensing and response capability. Using 20,000 repetitions, the 95% confidence interval (CI) ranged from 0.05797 (lower CI) to 0.5101 (upper CI) (see appendix D for distribution of indirect effects). The evidence confirms the fully mediated relationship between SCDO and disruption sensing and response capability. As SCDO is an operational level construct, we envision that employees need quality messages to comprehend SC objectives. Operationally, poor information quality leads to increased costs and undermines the satisfaction of both employees and customers (Redman, 1998).

### **Organizational learning (H3A-B)**

H3A hypothesized a positive relationship between organizational learning and the disruption sensing and response capability construct. The findings indicate that the direct path is significant and positive ( $\beta = 0.436$ ,  $p = 0.0224$ ). We expected this result, as the organizational learning literature suggests that activities such as practice and simulation affect SC capabilities. For example, Ngai, Chau, and Chan (2010) linked organizational learning to SC agility. In addition, research has also linked organizational learning to productivity and cost improvements (Hatch and Mowery, 1998) and product quality capabilities (Fine, 1986; Linderman et al., 2004).



With a significant direct relationship established in H3A, we can only test for a partially mediated relationship through information quality. The analysis, however, shows that linkage between the organizational learning and information quality construct to be non-significant ( $b = -0.327$ ). When factoring in the relationship between information quality and disruption sensing and response capability ( $b = 0.511$ ), we find the indirect total to be  $b = -0.167$ . Therefore, only the direct relationship exists between organizational learning and the disruption sensing and response capability construct. We confirm that the indirect relationship is non-significant using a bootstrap analysis (see appendix D for distribution of indirect effects). Using 20,000 repetitions, the 95% confidence interval (CI) ranged from -0.4404 (lower CI) to 0.0263 (upper CI). Since this range included zero (0), the indirect relationship is not significant.

#### **Routine rigidity (H4)**

For hypothesis #4, we proposed a negative relationship between routine rigidity and the disruption sensing and response capability construct. However, to determine the impact we include REVENUE, a proxy for organizational size. We believe a moderated relationship exists as the effect of routine rigidity depends on the organization size. Stated differently, as organization size increases, the effect of routine rigidity will also change. Both routine rigidity (IV) and REVENUE (moderating variable) were mean centered for the analysis. Upon examination, we find that the interaction routine rigidity X REVENUE negatively affects the direct relationship. Stated differently, there is a moderated relationship between routine rigidity and disruption sensing and response

capability when we account for REVENUE. Hence, we see a decrease in the slope by -0.105 for every unit increase for REVENUE. Thus, we find support for H4A.. While informative, this does not provide a complete understanding of what is occurring.

. To facilitate interpretation, we report simple slopes as suggested by Aiken and West (1992). As part of the analysis, we find a significant and positive direct relationship ( $\beta = 0.109$ ,  $p = 0.0272$ ) between routine rigidity and disruption sensing and response capability

- *Simple slope for disruption sensing and response capability at +3 standard deviations of REVENUE*  $= 0.109 + (-0.105 * +3 * 1.601) = -0.3953$
- *Simple slope for disruption sensing and response capability at +1 standard deviations of REVENUE*  $= 0.109 + (-0.105 * 1 * 1.601) = -0.05910$
- *Simple slope for disruption sensing and response capability at its mean*  $= 0.109$
- *Simple slope for disruption sensing and response capability at -1 standard deviations of REVENUE*  $= 0.109 + (-0.105 * -1 * 1.601) = 0.27710$

This indicates that at high REVENUE levels (larger organizations); a one-unit increase in routine rigidity decreases disruption sensing and response capability by 0.05910 units. At moderate levels of REVENUE, a one-unit change in routine rigidity slightly improves the disruption sensing and response capability by 0.104. Finally, when REVENUE levels are low (small organizations), a one-unit increase in routine rigidity improves the disruption sensing and response capability by 0.27710. Bala and Venkatesh (2007) had similar results in their study of routine rigidity and the dominance of firms. They found that non-dominant organizations are immune to routine rigidity effects, by developing a range of routines for different trading partners. Figure 4 illustrates the slope of the interaction at high (+1 standard deviations), medium (at mean), and low levels (-1 standard deviations). We also provide the simple slopes at +3 standard deviations to

illustrate extremely large organizations where the inertia literature suggests routine rigidity would be most prevalent.

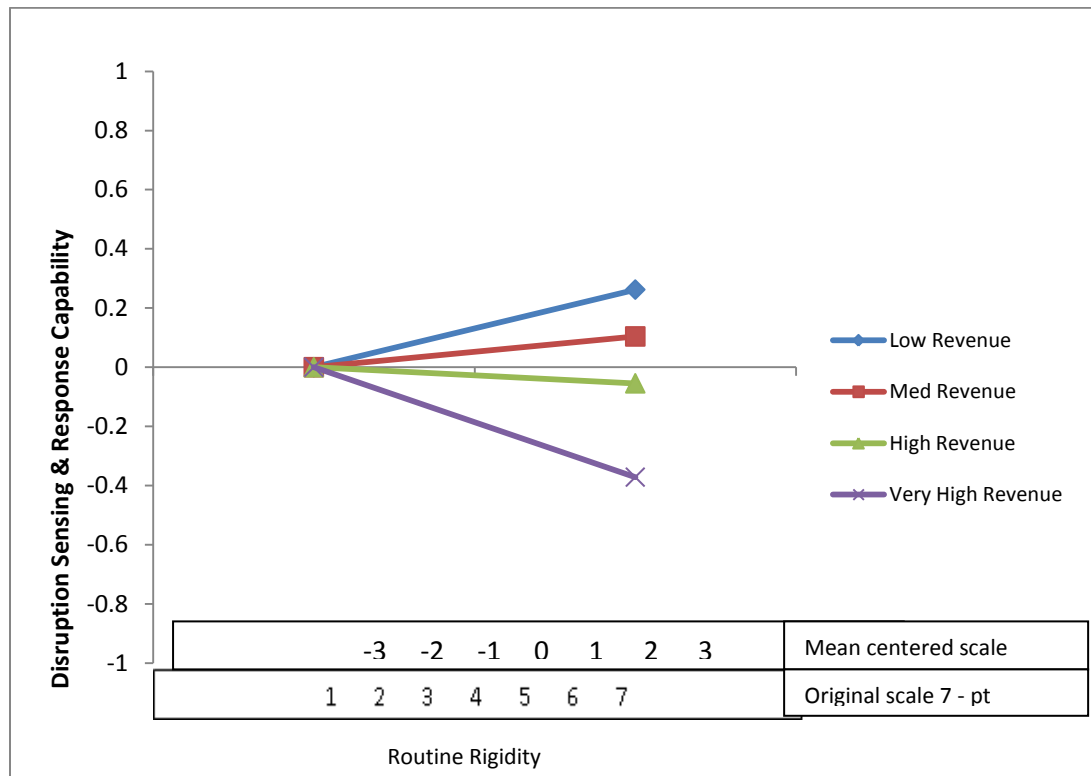


Figure 4: Simple Slopes for routine rigidity x REVENUE interaction

### Disruption sensing and response capability to organization performance (H5)

The path coefficient from disruption sensing and response capability to organization performance is positive, ( $\beta = 0.829$ ,  $p > 0.0001$ ). This suggests that managers can develop disruption sensing and response capabilities as a method to improve performance. This result also supports the assertions within the existing RM

literature suggesting that warning and recovery capabilities enhance performance (Craighead et al., 2007).

### The effect of control variables

We tested the effect related to several control variables: command center (COMMAND), experience (TENURE), position (RANK), and annual purchasing spend (SPEND) (See Table 13). None of the controls, COMMAND, TENURE, RANK, or SPEND, significantly altered the relationships found within the alternate model.

	COMMAND	RANK	TENURE	SPEND
Disruption Sensing & Response Capability	-0.267 (0.037)***	-0.011 (0.050)	-0.063 (0.059)	-0.143 (0.169)
Information Quality	0.127 (0.034)**	0.015 (0.067)	0.075 (0.062)	0.046 (0.056)
Organizational Performance	0.041 (0.043)	0.012 (0.067)	0.003 (0.076)	0.035 (0.092)
S-B Scaled Chi-Square	948.22	796.16	787.76	769.48
DEGREES OF FREEDOM	526	526	526	526
COMPARATIVE FIT INDEX (CFI)	0.882	0.916	0.919	0.925
NON-NORMED FIT INDEX (NNFI)	0.859	0.899	0.903	0.91
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)	0.063	0.05	0.049	0.048
90% CONFIDENCE INTERVAL OF RMSEA	(0.056-0.069)	(0.043-0.057)	(0.042-0.056)	(0.040-0.054)
Notes: *** Significant to 0.0001; ** Significant to 0.001;				

Table 13: Control variable betas, standard errors, and fit indices

### **Implications for Research and Practice**

Research into SCR and RM continues to expand as organizations realize the vulnerabilities of their elongated supply chains. While many studies examine operational mitigation techniques like buffers and capacity, there is scant research into organizational RM practices. In particular, there is a dearth of behavior-based RM techniques (Zsidisin, 2003; Simchi-Levi et al., 2010). Recognizing how organizations develop and embed these RM competencies and capabilities into the organization's culture is central to understanding future RM initiatives. By developing and empirically validating the disruption sensing and response capability measure, this study enhances future SCRM research in three ways. First, we provide an empirically valid and reliable measure that organization can use to measure and benchmark their RM capabilities. Second, the study confirms that organizations should develop their common vision, SCDO, and organizational learning competencies to enhance their RM capabilities. Third, the evidence implies that large organizations must manage their routine rigidity levels; otherwise, they may experience a degradation of their disruption sensing and response capabilities. Fourth, by teasing out the effect of information quality on the different relationships, managers understand the importance of quality communications. Lastly, the study provides empirical evidence, illustrating how managers can use behavior-based RM techniques.

## **Discussion**

While practitioners may suggest that an organization's common vision, SCDO, organizational learning, and routine rigidity competencies may affect its RM capabilities, there is scant evidence confirming the relationships. To fill this gap, we empirically test the effect of four antecedent competences and one mediating variable on the disruption sensing and response capability measure and organization performance. We provide confirmation that organizations can develop their common vision, SCDO, and organizational learning competencies as a way to address SC risk. These competencies allow managers to develop their employees and their abilities rather than just investing in redundancies such as inventory or capacity.

In addition, we offer a new multi-dimensional RM measure, which enables academics and practitioners to evaluate and compare a key RM capability. The measure uses Craighead's, (2007) definition and accounts for both a warning and recovery dimension. However, the evidence suggests that practitioners have a difficult time separating the warning and recovery dimensions. We recognize that we tested the constructs across multiple industries. Future research, where industry variance is controlled may lead to different results.

## **Limitations**

We acknowledge several methodological and conceptual limitations. The primary limitation of this work is that we derive our findings from 206 procurement directors and

managers. While we believe these respondents represent the larger population of procurement professionals, we suggest caution when interpreting the results.

Second, using a sample composed of organizations from different industries may be problematic. The sample's diversity may have caused the strength of specific relationships to be attenuated by industries with stronger or weaker relationships. We suspect that if this study focused on a single industry that the path coefficients found could be slightly different.

Third, while we triangulate this study with qualitative data from multiple rounds of item-to construct sorting procedures and interview feedback, we believe additional research is necessary. Researchers need to confirm the validity and reliability of the measurement items and this survey instrument.

A fourth limitation is that while our conceptualization of the disruption sensing and response capability measure advances our understanding of SCRM, we concede that other factors also influence an organization's RM capabilities. In particular, we did not test the manager's risk perception about how a threat affects an organization's disruption sensing and response capability. As this investigation's original objective was to operationalize the warning and recovery constructs, as proposed by Craighead et al. (2007), we felt appropriate to test the predictive validity of the newly proposed behavior-based RM tactic.

### **Future Research Opportunities**

We note three potential research opportunities that stem from this analysis. First, and most logical, is to investigate other organizational competencies, such as external SC integration or vertical information systems (Galbraith, 1974), which can be linked to an organization's disruption sensing and response capability. Second, we believe there is a wealth of opportunity to explore the proactive and reactive recovery capabilities that are proposed within our manuscript. Results from these opportunities will further augment the extant knowledge of SCRM frameworks and risk management practices. Third, we would like to see these same constructs tested within a single industry. We believe the results and supporting theory could provide additional insight into how an organizations and its industry deal with SC disruptions.

### **Conclusions**

Our results indicate that organizations can manage behavior-based competencies as a mechanism to improve their SCRM capabilities. We show, in particular, the value of developing an organization's common vision and SCDO. Managers use these competencies to outline the goals of an organization and provide energy and guidance as practitioners work to achieve these objectives. The evidence also suggests that enhanced organizational learning abilities allow practitioners to learn from and better prepare for SC disruption. With expanding supply chains and more complexity between the various nodes, SC practitioners need to be able to convert what they learn into new RM practices. At the same time, we found that controlling routine rigidity levels is important so



employees do not inhibit their adaptation and improvisation abilities, which help address unpredictable SC threats. The evidence suggests this is a significant issue within larger organizations. Managers need to prepare SC practitioners for disruption so they can respond quickly and adapt when necessary.

Beyond the findings specific to behavior-based competencies, this study contributes to the OM and RM literature in four ways. First, it validates a theory-based SCRM measure. The disruption sensing and response capability construct addresses both the warning and recovery dimension as proposed by Craighead et al., (2007). However, by confirming that the warning capability and recovery capability measures are not different, we provide evidence about how practitioners view SCRM. Specifically, the evidence indicates that while warning and recovery are conceptually different, that in practice, they are actually one RM concept. Second, we provide evidence of the connection between internal competencies, RM capabilities, and operating performance. This confirms high reliability theory theorists' belief that organizations can simultaneously focus on several objectives, such as performance and safety. Third, by studying the moderating effects of firm size and the mediating effects of information quality, we provide direction to managers as they develop RM strategies. As stated by Manuj and Mentzer (2008), "Managers must understand the advantages and disadvantages of the various risk management strategies, and when they are appropriate" (p. 216). Lastly, by studying the behavior-based competencies and capabilities, we further the principle that organizations should embed an understanding of RM and risk assessment into their culture (Simchi-Levi, 2010). Managers should design daily

activities that enhance organizational learning, information quality, and communication with RM initiatives in mind. Otherwise, SC practitioners and the organization will not be prepared for the next inevitable SC disruption.

By developing behavior based competencies and capabilities to the arsenal of RM tactics, organizations can better protect their supply chains from inevitable disruptions. These RM techniques are particularly helpful for when SC threats rarely occur and when they do, they manifest in unpredictable ways. We hope managers embed these behaviors into the culture of an organization so practitioners can adapt and overcome any type of SC threat, large or small.

## **Appendices**

### **Appendix A: Survey questions**

#### *Common vision*

1. The management team has clearly explained our organization's vision.
2. Most employees are aware of my organization's primary business goals and objectives.
3. Most employees value my organization's goals and objectives.
4. When setting goals, most employees consider the organization's vision.

#### *Supply chain disruption orientation*

5. Understanding how supply chain disruptions occur is important to my organization.
6. As an organization, we regularly think about supply chain disruptions.
7. We think about how supply chain disruptions can be avoided across the organization.
8. Supply chain disruptions show my organization where we can improve.

#### *Organizational learning*

9. Within my organization, learning is key to improvement.
10. As an organization, we learn from our experiences.
11. Our ability to learn is the key to improving my organization.
12. As an organization, we learn from our successes.

### *Routine rigidity*

- 13. There is resistance within my organization when trying to change existing business processes.
- 14. Within my organization, there are many overlapping processes.
- 15. I have a tendency to resist changing how I am used to doing things within my organization.
- 16. I find it difficult to learn new processes.

### *Information quality*

- 17. Within my organization, information used for analysis and reporting is reliable.
- 18. Within my organization, information used for analysis and reporting is timely.
- 19. Within my organization, information used for analysis and reporting is accurate.

### *Warning capability*

- 20. My organization has procedures to identify threats.
- 21. Within my organization, there are systems to warn employees about potential threats.
- 22. Within my organization, the command center identifies actual disruptions.
- 23. The command center identifies potential threats.

### *Recovery capability*

- 24. When a disruption occurs, my organization immediately starts recovery efforts.
- 25. Once a threat is identified, my organization deploys resources to reduce the negative effects.

26. My organization's command center deploys recovery resources to reduce the effects of a disruption.

27. Resources can be deployed before an actual disruption occurs.

*Performance*

28. My organization is able to keep operating costs to a minimum.

29. My organization is able to keep out of stocks to a minimum.

30. My organization is able to keep service quality high.

*Control questions*

31. Does your organization have an emergency command / center or disaster response center?

32. Position within the firm?

33. Years / of professional work experience?

34. Annual purchasing spend (approximate).

35. Annual revenues (approximate).

## **Appendix B: Data collection procedures**

In this study, we used Empanelonline.com to administer the data collection process. With access to 1.3 million potential respondents, Empanelonline.com, uses a “double opt-in” procedure to register and survey qualified panelists. Initially, prospective respondents join various panels by registering at Empanelonline.com. Respondents identify panels for which they are qualified, by answering questions about their credentials (experience, job title, household income, etc.) Once qualified Empanelonline.com invites respondents to complete questionnaires that pertain to certain topics (i.e. the join certain panels. Empanelonline.com does conduct verification checks to determine if respondents’ are genuine. This includes validating address and email information and verifying respondents against third-party databases when possible. Further, Empanelonline.com periodically reviews the quality of respondents to ensure that panelists are qualified to answer survey. This includes monitoring how many surveys the panelist has completed and qualification questions about certain topics. Lastly, Empanelonline.com does monitor professional survey takers and removes them from all available panels.

The population of interest for our study was procurement/purchasing decision makers such as procurement director, purchasing managers and procurement analysts. Empanelonline.com invited respondents from a random sample of qualified panel members: procurement/purchasing professionals. The email invitation explained the research objective, presented a hyperlink to the actual survey, offered a time estimate to complete the survey, provided contact information pertaining to the primary researcher,

described the incentive to complete the survey, and offered opt-out information.

Empanelonline.com offers respondents incentive points to complete the survey.

We targeted respondents who devoted 50% or more of their time to procurement/purchasing activities and were from organizations with at least 50 employees. To ensure that panelists matched this frame, we embedded two screening questions into the survey. These were the first two questions asked. If panelists responded that less than 50% of their time was devoted to procurement/purchasing activities or they worked for organizations with less than 50 employees, the survey concluded and thanked respondents for their participation. All others respondents were allowed to continue answering survey questions.

#### *Qualification #1*

How much time on a weekly basis do you spend with procurement/purchasing duties?

Less than < 50% -(Survey concluded and thanked respondents for their participation)

Between 50 and 75% -(Respondents were allowed to continue answering survey questions)

Between 75 and 90% -(Respondents were allowed to continue answering survey questions)

Greater than >90% -(Respondents were allowed to continue answering survey questions)

#### *Qualification #2*

How many employees in your organization?

< 50% -(Survey concluded and thanked respondents for their participation)

50-999 -(Respondents were allowed to continue answering survey questions)

1,000-9,999 -(Respondents were allowed to continue answering survey questions)

10,000-49,999 -(Respondents were allowed to continue answering survey questions)

50,000-99,999 -(Respondents were allowed to continue answering survey questions)

100,000-249,999 -(Respondents were allowed to continue answering survey questions)

>250,000 -(Respondents were allowed to continue answering survey questions)

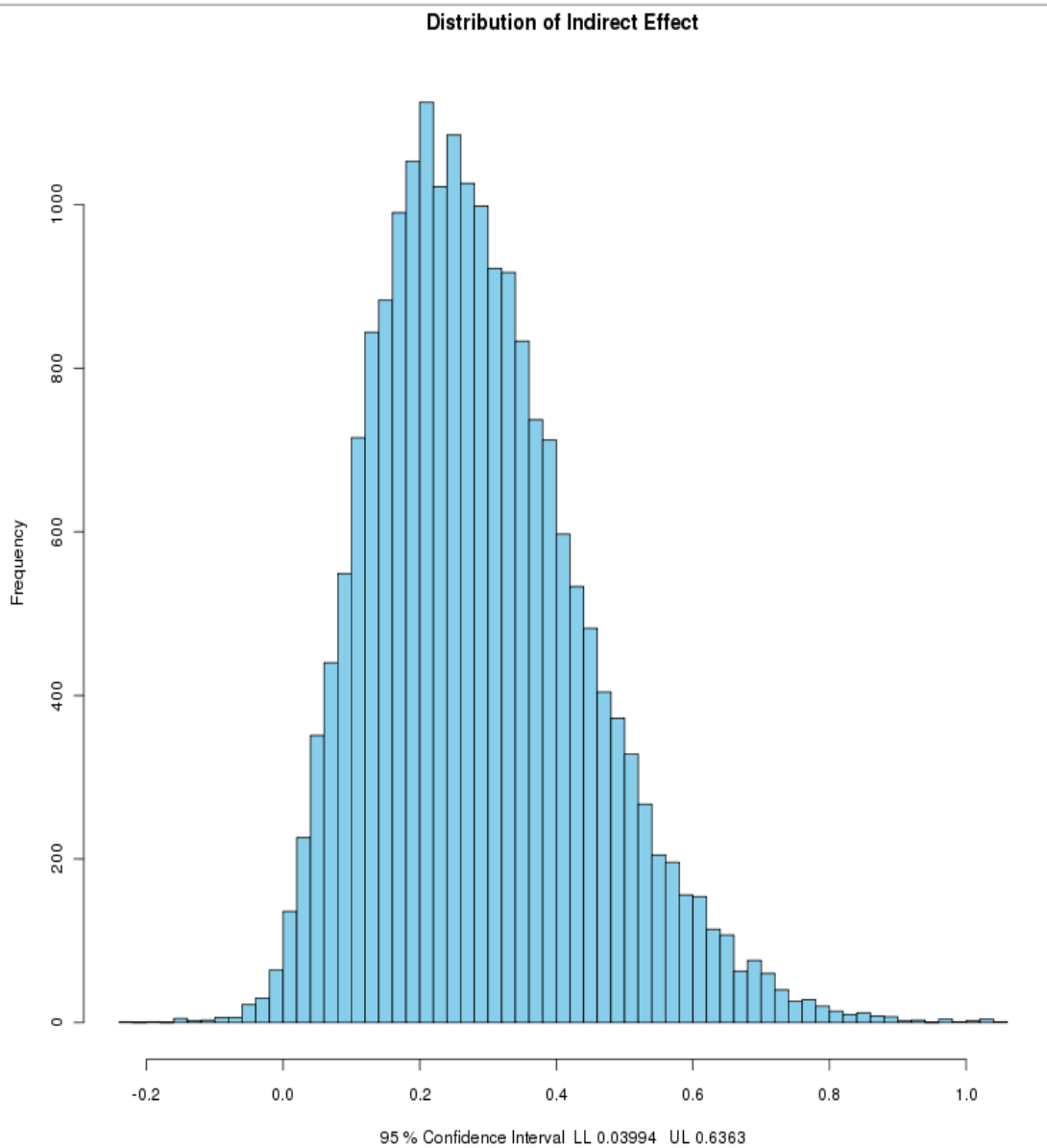


### Appendix C: Latent factor and marker variable test

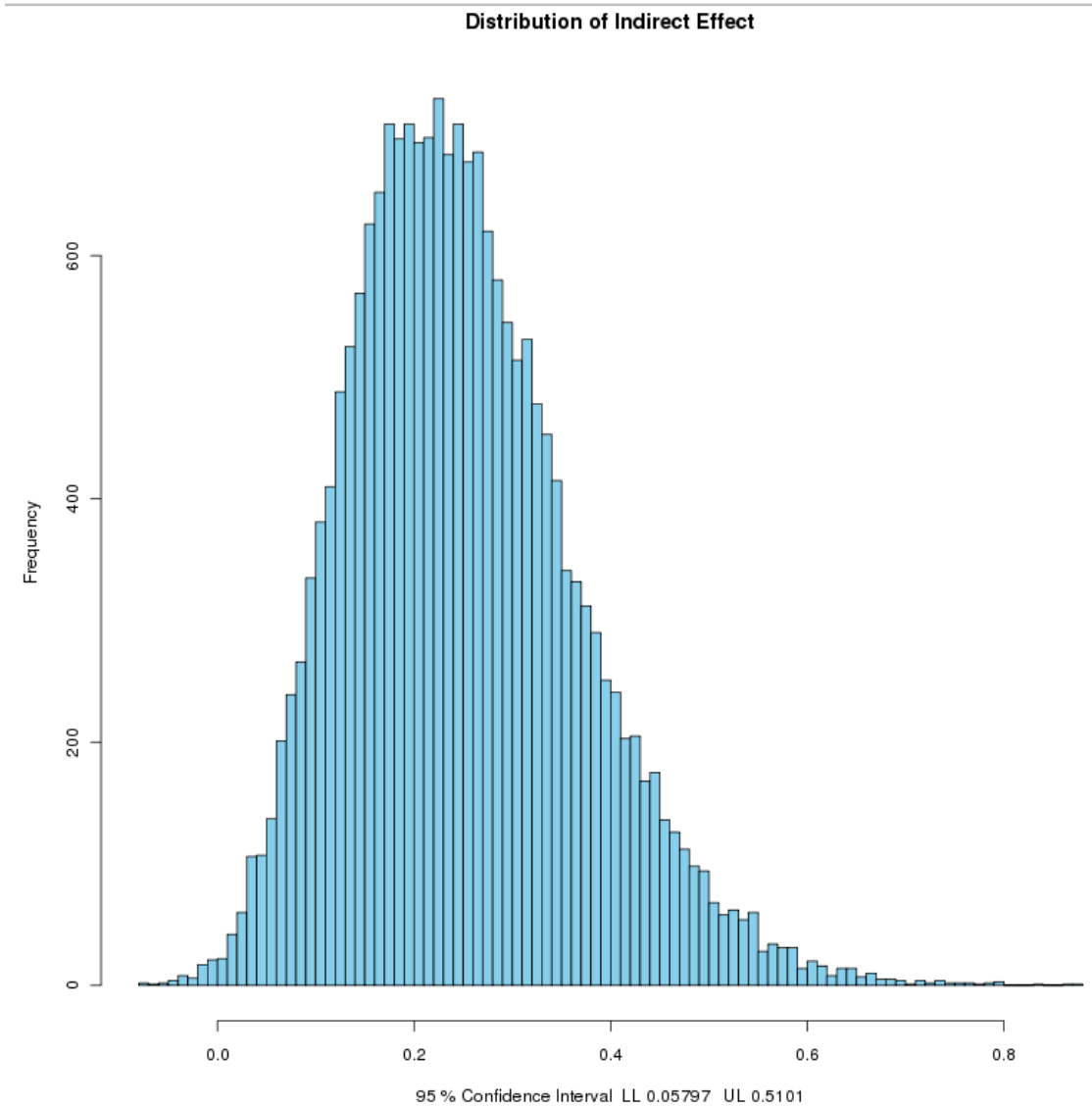
Factor	Item	Trait Loading	Trait Loading	Sqd Method Loadings	Trait Loading	Sqd Marker Loadings
Common Vision	CV1	0.827	0.741	0.174	0.757	0.095
	CV2	0.813	0.81	0.030	0.734	0.104
	CV3	0.818	0.799	0.039	0.756	0.086
	CV4	0.752	0.762	0.013	0.671	0.096
Organizational Learning	OL1	0.757	0.623	0.212	0.717	0.050
	OL2	0.837	0.802	0.048	0.808	0.048
	OL3	0.849	0.755	0.135	0.798	0.070
	OL4	0.803	0.785	0.030	0.757	0.061
Performance	PER1	0.648	0.649	0.026	0.513	0.114
	PER2	0.757	0.781	0.011	0.63	0.132
	PER3	0.799	0.744	0.051	0.737	0.102
Disruption Management Capabilities	WC1	0.807	0.664	0.311	0.732	0.104
	WC2	0.793	0.723	0.114	0.713	0.104
	WC3	0.819	0.831	0.019	0.73	0.115
	WC4	0.808	0.864	0.001	0.706	0.125
	RC1	0.787	0.705	0.088	0.687	0.127
	RC2	0.828	0.691	0.142	0.763	0.100
	RC3	0.814	0.705	0.132	0.719	0.129
	RC4	0.706	0.743	0.019	0.582	0.129
Information Quality	IQ1	0.918	0.79	0.289	0.85	0.123
	IQ2	0.808	0.766	0.077	0.72	0.110
	IQ3	0.79	0.799	0.039	0.699	0.109
Routine Rigidity	RR1	0.725	0.741	0.027	0.681	0.050
	RR2	0.684	0.702	0.034	0.655	0.025
	RR3	0.894	0.882	0.000	0.875	0.037
	RR4	0.774	0.775	0.023	0.73	0.066
Supply Chain Disruption	SCD1	0.868	0.697	0.329	0.798	0.119
	SCD2	0.778	0.675	0.176	0.661	0.137
	SCD3	0.727	0.742	0.033	0.624	0.106
	SCD4	0.649	0.679	0.020	0.559	0.081
AVE		0.677	0.632		0.594	
Chi-square		894.68	718.65		912.64	
Chi-square (S-B)		602.61	516.44		612.36	
df		377	347		377	
CFI (S-B)		0.918	0.938		0.915	
RMSEA (S-B)		0.054	0.049		0.055	
RSMR		0.048	0.041		0.072	

## Appendix D: Bootstrap tests for indirect effects

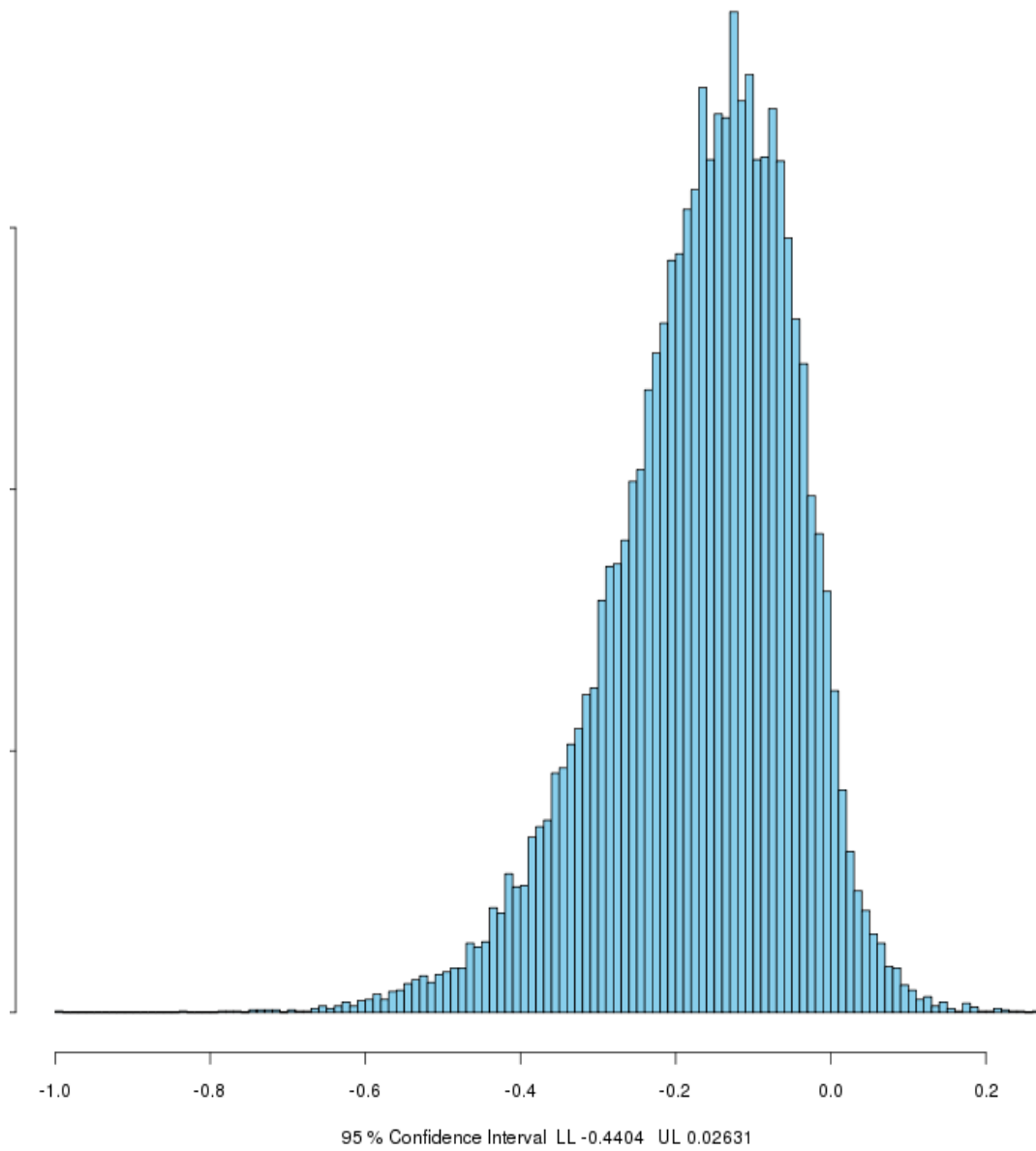
*Distribution of indirect effect for the common vision – information quality – disruption sensing and response capability relationship*



*Distribution of Indirect Effect for the SCDO – information quality – disruption sensing and response capability relationship*



*Distribution of Indirect Effect for the organizational learning – information quality –  
disruption sensing and response capability relationship*



## **Appendix E: Satorra-Bentler difference input & output variables**

### *Common vision and organizational learning*

Satorra-Bentler chi square for the MORE constrained model= 555.92

Normal chi square for the MORE constrained model= 758.63

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 758.639

Satorra-Bentler chi square for the RETEST model = 555.872

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 30.3126186

### *Common vision and PERF*

Satorra-Bentler chi square for the MORE constrained model= 540.3314

Normal chi square for the MORE constrained model= 746.252

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 746.260

Satorra-Bentler chi square for the RETEST model = 540.311

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 20.30977216

*Common vision and warning capability*

Satorra-Bentler chi square for the MORE constrained model=594.9573

Normal chi square for the MORE constrained model= 795.502

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 795.509

Satorra-Bentler chi square for the RETEST model = 594.9518

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 1.656345401

*Common vision and recovery capability*

Satorra-Bentler chi square for the MORE constrained model=559.2729

Normal chi square for the MORE constrained model= 774.131

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 774.138

Satorra-Bentler chi square for the RETEST model = 559.4283

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 36.64751981

*Common vision and information quality*

Satorra-Bentler chi square for the MORE constrained model= 526.9013

Normal chi square for the MORE constrained model= 778.294

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.2784

Normal chi square for the LESS constrained model= 718.675

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 778.297

Satorra-Bentler chi square for the RETEST model = 526.998

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 37.99411042

*Common vision and routine rigidity*

Satorra-Bentler chi square for the MORE constrained model=517.97

Normal chi square for the MORE constrained model= 779.48

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 779.484

Satorra-Bentler chi square for the RETEST model = 517.8528

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 43.93457245

*Common vision and SCDO*

Satorra-Bentler chi square for the MORE constrained model= 563.4334

Normal chi square for the MORE constrained model= 783.997

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674



Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 784.005

Satorra-Bentler chi square for the RETEST model = 563.6130

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 42.40656099

### *Organizational learning and PERF*

Satorra-Bentler chi square for the MORE constrained model=544.5128

Normal chi square for the MORE constrained model= 744.750

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 744.756

Satorra-Bentler chi square for the RETEST model = 544.3480

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 21.36980586

*Organizational learning and warning capability*

Satorra-Bentler chi square for the MORE constrained model=511.767

Normal chi square for the MORE constrained model= 767.120

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 767.126

Satorra-Bentler chi square for the RETEST model = 511.7825

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 32.06967312

*Organizational learning and recovery capability*

Satorra-Bentler chi square for the MORE constrained model= 550.23

Normal chi square for the MORE constrained model= 771.88

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 771.88

Satorra-Bentler chi square for the RETEST model = 550.21

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 38.41208166

*Organizational learning and information quality*

Satorra-Bentler chi square for the MORE constrained model=508.9184

Normal chi square for the MORE constrained model= 759.199

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 759.1992

Satorra-Bentler chi square for the RETEST model = 508.9184

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 27.16536529

*Organizational learning and routine rigidity*

Satorra-Bentler chi square for the MORE constrained model=515.20

Normal chi square for the MORE constrained model= 780.35

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 515.7481

Normal chi square for the LESS constrained model= 718.658

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 780.355

Satorra-Bentler chi square for the RETEST model = 515.2626

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 39.14806243

#### *Organizational learning and SCDO*

Satorra-Bentler chi square for the MORE constrained model=529.0177

Normal chi square for the MORE constrained model= 777.754

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 777.76

Satorra-Bentler chi square for the RETEST model = 529.1026

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 38.17300317

*PERF and warning capability*

Satorra-Bentler chi square for the MORE constrained model= 567.55

Normal chi square for the MORE constrained model= 769.24

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 769.24

Satorra-Bentler chi square for the RETEST model = 567.57

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 36.85723134

*PERF and recovery capability*

Satorra-Bentler chi square for the MORE constrained model= 537.8265

Normal chi square for the MORE constrained model= 739.744

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 739.749

Satorra-Bentler chi square for the RETEST model = 537.7272

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 877128

*PERF and information quality*

Satorra-Bentler chi square for the MORE constrained model= 554.7522

Normal chi square for the MORE constrained model= 764.886

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 764.887

Satorra-Bentler chi square for the RETEST model = 554.6510

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 35.79916029

*PERF and routine rigidity*

Satorra-Bentler chi square for the MORE constrained model=546.8164

Normal chi square for the MORE constrained model= 797.850

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 797.857

Satorra-Bentler chi square for the RETEST model =546.821

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 54.27522009

#### *PERF and SCDO*

Satorra-Bentler chi square for the MORE constrained model=553.5108

Normal chi square for the MORE constrained model= 772.355

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 515.7481

Normal chi square for the LESS constrained model= 718.658

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 772.363

Satorra-Bentler chi square for the RETEST model = 553.5256

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference =38.26464361

*Warning capability and recovery capability*

Satorra-Bentler chi square for the MORE constrained model= 528.7864

Normal chi square for the MORE constrained model= 732.579

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 515.7481

Normal chi square for the LESS constrained model= 718.658

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 732.583

Satorra-Bentler chi square for the RETEST model = 528.9370

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 9.160674837

*Warning capability and information quality*

Satorra-Bentler chi square for the MORE constrained model=510.1897

Normal chi square for the MORE constrained model= 760.114

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674



Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 760.120

Satorra-Bentler chi square for the RETEST model = 510.2841

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 26.21433738

*Warning capability and routine rigidity*

Satorra-Bentler chi square for the MORE constrained model=548.9498

Normal chi square for the MORE constrained model= 797.376

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 797.378

Satorra-Bentler chi square for the RETEST model = 548.7743

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 61.01737605

*Warning capability and SCDO*

Satorra-Bentler chi square for the MORE constrained model=518.9067

Normal chi square for the MORE constrained model= 769.093

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 769.095

Satorra-Bentler chi square for the RETEST model = 518.8685

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 34.95294823

*Recovery capability and information quality*

Satorra-Bentler chi square for the MORE constrained model=569.7315

Normal chi square for the MORE constrained model= 788.710

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 788.712

Satorra-Bentler chi square for the RETEST model = 569.7873

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 48.98127499

*Recovery capability and routine rigidity*

Satorra-Bentler chi square for the MORE constrained model=519.5856

Normal chi square for the MORE constrained model= 781.188

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 781.190

Satorra-Bentler chi square for the RETEST model = 519.6151

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 40.82216157

*Recovery capability and SCDO*

Satorra-Bentler chi square for the MORE constrained model=509.4189

Normal chi square for the MORE constrained model= 759.960

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 759.964

Satorra-Bentler chi square for the RETEST model = 509.3705

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 28.68384106

*Information quality and routine rigidity*

Satorra-Bentler chi square for the MORE constrained model=511.3064

Normal chi square for the MORE constrained model= 763.065

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 763.069

Satorra-Bentler chi square for the RETEST model = 511.2599

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 30.78329397

*Information quality and SCDO*

Satorra-Bentler chi square for the MORE constrained model=564.6754

Normal chi square for the MORE constrained model= 787.591

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 787.597

Satorra-Bentler chi square for the RETEST model = 564.7379

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 47.71625524

*Routine rigidity and SCDO*

Satorra-Bentler chi square for the MORE constrained model=528.2703

Normal chi square for the MORE constrained model= 779.084

Degrees of freedom for the MORE constrained model= 348

Satorra-Bentler chi square for the LESS constrained model= 516.6214

Normal chi square for the LESS constrained model= 718.674

Degrees of freedom for the LESS constrained model= 347

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 779.088

Satorra-Bentler chi square for the RETEST model = 528.1042

DF =347

OUTPUTS: Satorra-Bentler Scaled Difference = 46.08455649

## **Appendix F: Difference input & output variables-amended model**

### *Common vision and organizational learning*

Satorra-Bentler chi square for the MORE constrained model= 563.2584

Normal chi square for the MORE constrained model= 782.230

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 782.233

Satorra-Bentler chi square for the RETEST model = 563.2083

DF =354

OUTPUTS: Satorra-Bentler Scaled Difference = 21.43247838

### *Common vision and PERF*

Satorra-Bentler chi square for the MORE constrained model= 564.0833

Normal chi square for the MORE constrained model= 780.354

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 780.356

Satorra-Bentler chi square for the RETEST model = 564.1165

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference = 21.29363171

*Common vision and disruption sensing and response capability*

Satorra-Bentler chi square for the MORE constrained model= 619.0092

Normal chi square for the MORE constrained model= 834.593

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 834.597

Satorra-Bentler chi square for the RETEST model = 618.8700

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference = 56.99258656

*Common vision and information quality*

Satorra-Bentler chi square for the MORE constrained model= 551.6694



Normal chi square for the MORE constrained model= 814.253

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 814.258

Satorra-Bentler chi square for the RETEST model = 551.6002

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference = 40.62832603

#### *Common vision and routine rigidity*

Satorra-Bentler chi square for the MORE constrained model= 553.5034

Normal chi square for the MORE constrained model= 826.172

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 826.175

Satorra-Bentler chi square for the RETEST model = 553.6120

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference = 53.70839089

*Common vision and SCDO*

Satorra-Bentler chi square for the MORE constrained model= 584.8063

Normal chi square for the MORE constrained model= 814.209

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 814.212

Satorra-Bentler chi square for the RETEST model = 584.9173

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference = 48.23821762

*Organizational learning and PERF*

Satorra-Bentler chi square for the MORE constrained model= 562.8300

Normal chi square for the MORE constrained model= 775.823

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 775.828

Satorra-Bentler chi square for the RETEST model = 562.7870

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference = 17.15182138

*Organizational learning and disruption sensing and response capability*

Satorra-Bentler chi square for the MORE constrained model= 541.4671

Normal chi square for the MORE constrained model= 807.015

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 807.017

Satorra-Bentler chi square for the RETEST model = 541.4443

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference = 36.67732463

*Organizational learning and information quality*

Satorra-Bentler chi square for the MORE constrained model= 529.1605

Normal chi square for the MORE constrained model= 785.731

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 785.735

Satorra-Bentler chi square for the RETEST model = 529.0224

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference = 21.07248324

### *Organizational learning and routine rigidity*

Satorra-Bentler chi square for the MORE constrained model= 548.7043

Normal chi square for the MORE constrained model= 815.818

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 815.819

Satorra-Bentler chi square for the RETEST model = 548.7128

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference = 43.48943649

*Organizational learning and SCDO*

Satorra-Bentler chi square for the MORE constrained model= 532.9881

Normal chi square for the MORE constrained model= 795.971

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 795.973

Satorra-Bentler chi square for the RETEST model = 532.9665

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference = 29.3398602

*PERF and Disruption sensing and response capability*

Satorra-Bentler chi square for the MORE constrained model= 577.5904

Normal chi square for the MORE constrained model= 788.827

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 788.839

Satorra-Bentler chi square for the RETEST model = 577.6336

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference =27.9331226

*PERF and information quality*

Satorra-Bentler chi square for the MORE constrained model=580.1387

Normal chi square for the MORE constrained model= 800.582

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 800.586

Satorra-Bentler chi square for the RETEST model = 579.9547

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference =31.92555118

*PERF and routine rigidity*

Satorra-Bentler chi square for the MORE constrained model=579.1166

Normal chi square for the MORE constrained model= 835.613

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 835.614

Satorra-Bentler chi square for the RETEST model =

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference =54.00036943

*PERF and SCDO*

Satorra-Bentler chi square for the MORE constrained model=577.8011

Normal chi square for the MORE constrained model= 805.368

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 805.372

Satorra-Bentler chi square for the RETEST model = 578.0100

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference =44.2580408

*Disruption sensing and response capability and information quality*

Satorra-Bentler chi square for the MORE constrained model=543.9091

Normal chi square for the MORE constrained model= 803.219

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 803.221

Satorra-Bentler chi square for the RETEST model = 543.9561

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference =36.10791978

*Disruption sensing and response capability and routine rigidity*

Satorra-Bentler chi square for the MORE constrained model=552.1511



Normal chi square for the MORE constrained model= 841.459

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 841.462

Satorra-Bentler chi square for the RETEST model = 552.3095

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference =65.63925219

*Disruption sensing and response capability and SCDO*

Satorra-Bentler chi square for the MORE constrained model=545.5732

Normal chi square for the MORE constrained model= 814.523

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 814.527

Satorra-Bentler chi square for the RETEST model = 545.6578

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference =44.60035413

*Information quality and routine rigidity*

Satorra-Bentler chi square for the MORE constrained model=540.5755

Normal chi square for the MORE constrained model= 802.196

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 802.199

Satorra-Bentler chi square for the RETEST model = 540.6051

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference =34.80287969

*Information quality and SCDO*

Satorra-Bentler chi square for the MORE constrained model=557.2890

Normal chi square for the MORE constrained model= 817.699

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 817.704

Satorra-Bentler chi square for the RETEST model = 557.3354

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference =46.39760723

### *Routine rigidity and SCDO*

Satorra-Bentler chi square for the MORE constrained model=541.9344

Normal chi square for the MORE constrained model= 809.503

Degrees of freedom for the MORE constrained model= 355

Satorra-Bentler chi square for the LESS constrained model= 535.5959

Normal chi square for the LESS constrained model= 751.485

Degrees of freedom for the LESS constrained model= 354

Unconstrained Model with start values from Model 2 and iterations=0

Normal chi square for the RETEST model= 809.506

Satorra-Bentler chi square for the RETEST model = 541.9454

DF =355

OUTPUTS: Satorra-Bentler Scaled Difference =39.0711807

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# **ORGANIZATIONAL STRUCTURE AND WARNING AND RECOVERY CAPABILITIES- A HOSPITAL PERSPECTIVE**

## **Abstract**

Risk experts suggest that organizations employ an array of mitigation techniques to manage supply chain risk. However, most studies focus on buffers and/or capacity as the primary risk management instrument. Therefore, following the recommendation of Zsidisin (2003) and Simchi-Levi, Kaminsky, and Simchi-Levi (2010), we investigated behavior-based capabilities, such as supply chain risk management tactics. To do this, we operationalized the warning and recovery measures proposed by Craighead, Blackhurst, Rungtusanatham, and Handfield (2007). We used a judgment-based sorting process, factor analysis, and survey data from hospital material managers to establish the measure's unidimensionality, reliability, and validity.

Furthermore, we studied how three competencies, internal integration, training, and information sharing, affect the warning and recovery constructs. These competencies provide structure, allow practitioners to connect and share information, and enable backup systems during SC disruptions (Bellamy, Crawford, Marshall, & Coulter, 2005; Reason, 2000; Rochlin, LaPorte, & Roberts, 1987).

The results indicated that internal integration and training positively affect the warning and recovery constructs. Our findings also indicated that managers should develop risk management capabilities, such as warning and recovery. First, the new measures allow practitioners and academics to assess an organizations' warning and recovery capabilities. Second, our study provides evidence that the two risk management

measures positively affect an organization's performance. Both findings are important for managers who seek alternative risk management techniques that would have a positive effect on performance.



## **Introduction**

Organizations develop complex and extended supply chains to reduce costs, connect with suppliers, and offer products and services to customers. However, as managers experiment with different supply chain (SC) configurations, they must consider that the risk of disruption rises as complexity increases (Manuj & Mentzer, 2008). Risk management (RM) experts also suggest that the probability of disruption increases as the SC becomes more integrated (Handfield, Blackhurst, Craighead, & Elkins, 2006; Norrman & Jansson, 2004). In such coupled networks, disruption consequences can travel quickly throughout a SC network. We believe that most organizations expend resources to reduce the negative effects of disruption consequences.

We argue that organizations should develop behavior-based capabilities and competencies to manage supply chain risk (SCR). Warning and recovery capabilities are proposed to enable rapid disruption identification and response while organizational competencies, such as information sharing (INFOSHR), internal integration, and training (TRAIN), provide structure, enhance internal connectedness, and enable backup system initiation (Bellamy et al., 2005; Reason, 2000; Rochlin, LaPorte, & Roberts, 1987).

The extant literature suggests that organizations can use behavior-based RM techniques to mitigate and even eliminate SC threats (Cheng, Yip, & Yeung, 2012; Simchi-Levi et al., 2010; Zsidisin, 2003). However, only a few researchers investigated the use of behavior-based tactics, such as RM mechanisms, directly. Examples include supplier certification (Lockhart & Ettkin, 1993; Zsidisin & Ellram, 2003), supplier development (Hartley & Choi, 1996; Watts & Hahn, 1993), target costing (Zsidisin &

Ellram, 2003), and quality development programs (Choi & Liker, 1995; Zsidisin & Ellram, 2003).

Following the logic espoused by high reliability theory (HRT), we argue that hospitals can use behavior-based tactics to reduce SCR by enhancing the internal coordination and structural coupling within the SC (Smart, Tranfield, Deasley, Levene, Rowe, & Corley, 2003). With this theoretical frame, we address three questions. First, can we develop psychometrically valid measures for warning and recovery capabilities? Second, do certain structural competencies improve a hospital's warning and recovery capabilities? Third, do enhanced warning and recovery capabilities lead to improved performance?

To answer these questions, we collected survey data from 215 hospital material and risk managers with an aim to investigate the relationships among various competencies, capabilities, and performance measures. We sought to understand the relationship among specific antecedent competencies and the warning and recovery constructs. Warning capabilities (WARN) reflect an organization's ability to scan for and communicate information about SC threats while recovery capabilities (RECOVR) refer to the pre-emptive and reactive response practices (Craighead et al., 2007).

We employed Noar's (2003) construct development process to operationalize the warning and recovery measures proposed by Craighead et al. (2007). We used qualitative feedback, judgment-based sorting processes (Q-sort), and confirmatory factor analysis to establish unidimensionality, reliability, and validity of the measures.

This study's aim was to gather insight on RM and SCRM practices within hospitals. With mandates to simultaneously reduce costs and improve quality, healthcare managers are actively seeking methods to minimize inventory and risk while delivering world-class service. McKone-Sweet, Hamilton, and Willis (2005) indicated that nearly 40% of a hospital's budget, in general, supports SC expenditures. Therefore, by developing behavior-based techniques, hospitals can improve their RM capabilities by enhancing their organization rather than investing in dollar intensive inventory.

This contribution is unique, as it suggests that organizations can develop competencies to improve their RM capabilities. Within healthcare operations, competencies, including internal integration, TRAIN, and INFOSHR, are necessary practices. Further, managers can justify investment in competencies rather than tangibles, such as inventory or capacity (Jüttner, Peck, & Christopher, 2003), as a way to reduce disruption risk.

### **Outline of the manuscript**

First, we review high reliability theory along with the relevant SC and RM literature in section 2. In section 3, we discuss the proposed model and hypotheses. Section 4 addresses methodological and statistical issues. Section 5 discusses the research findings. Further, in section 6 and 7, we discuss the limitations of our study and potential future research avenues.

## **Literature Review**

Within this section, we review conceptual tenets of high reliability theory that are pertinent to this research. In addition, we differentiate between several key components of risk and risk management. Lastly, discuss the dimensions of warning and recovery capabilities and establish their importance to this research.

### **High reliability theory (HRT)**

*High reliability theory* (HRT) postulates that an organization can avoid accidents indefinitely by designing systems that emphasize reliability rather than efficiency. HRT theorists describe how highly coupled and complex systems regularly face catastrophic disasters yet thrive over time (Rochlin, LaPorte, & Roberts, 1987; Weick & Roberts, 1993). Initial research venues included aircraft carriers (Rochlin, LaPorte, & Roberts, 1987), submarines (Bierly & Spender, 1995), nuclear power plants (Roth, 1997), and space shuttles (Marais, Dulac, & Leveson, 2004). These concepts have evolved and are now applied to product safety within supply chains (Speier, Whipple, Closs, & Voss, 2011), lean management (Marley, 2006), and emergency decision-making (White, Turoff, & Van de Walle, 2007).

While others have used HRT to frame RM research within healthcare settings, no one has used the theory to investigate SC risk within hospitals. Carroll and Rudolph (2006) sought to improve safety performance within healthcare organizations by using design principles from HRT. Similarly, Tamuz and Harrison (2006) framed their patient safety investigations using HRT tenets. Therefore, we seek to determine how hospital

supply chains use behavior based RM techniques to mitigate risk within the hospital supply chain. We argue that hospitals foster a culture of reliability, encourage practitioners to learn from accidents and near misses (La Porte & Consolini, 1991), and value redundancy (Rochlin et al., 1987). Further, while advocates pontificate that system reliability is above all else, we find that most highly reliable organizations value both performance and reliability equally (La Porte & Consolini, 1991).

Managers should draw on decoupling design principles, reliability oriented management practices, and a mindful organizational culture to sustain a highly reliable organization over time. Decoupled design principles refer to structures that seamlessly enable backup processes and systems (Bellamy et al., 2005; Reason, 2000; Rochlin, LaPorte, & Roberts, 1987). This includes practices that integrate and share information from multiple sources simultaneously. Reliability oriented management practices refer to a decentralized system where employees are empowered to make quick decisions rather than escalating to a centralized hierarchy (Bellamy et al., 2005). In the HRT environment, employees should be able to make timely decisions to maintain safety and save lives. “Mindful” practitioners are oriented towards learning from failures; they are committed to resilience and avoid simple interpretations that may lead to mishaps and near misses (Bellamy et al., 2005; Weick, Sutcliffe, & Obstfeld, 1999). Mindfulness equates to a preoccupation with avoiding failure and latitude for individual improvisation (Bellamy et al., 2005; Beyea, 2004).

We adopt the conceptual tenets of HRT, as it advocates how to operate a complex system, such as a hospital SC. Several tenets of the theory align with the aims of our

investigations. In particular, we seek to understand the effects of organizational structures, such as internal integration and training, on certain RM capabilities. Training, for instance, illustrates how practitioners respond to threats while internal integration reflects a connectedness tactic that enables employees and systems to work together.

To anchor our investigation to current risk and SC management thinking, we review existing risk, SCR, and SCRM literature. We then discuss warning and recovery capabilities before we operationalize the constructs and developed related hypotheses. We also segregate the two RM capability constructs into various dimensions and adopt appropriate definitions.

## **Risk**

*Risk* refers to unplanned variability associated with an outcome, and it “can be viewed as an expected value - the product of impact and probability” (Zsidisin, Melnyk, & Ragatz, 2005, p.3403). Previous research suggests that organizations should develop strategies to manage risk, absorb disruption consequences, or enable quick recovery (Tang, 2006). By developing these tactics proactively, organizations can prepare for an inevitable SC disruption (Knemeyer, Zinn, & Eroglu, 2009).

Only a few operations management researchers have developed risk measures. Ellis, Henry, and Shockley (2010) operationalized the measures of the magnitude and the probability of supply disruption along with providing details about the overall level of disruption risk. Several measures of operational failures associated with nurses are germane to the hospital context (Tucker, 2004). This research categorizes interruption,

delay, risk, and losses as dimensions of failure and measures actions that affect patient outcomes.

### **Supply chain risk**

According to Juttner et al. (2003), *supply chain risk* (SCR) describes risks associated with the movement of information, raw materials, or finished product as they flow from suppliers to consumers. Understanding that variability exists within all systems, SCR describes threats that create variability beyond planned levels. We believe that variability negatively affects operations and forces managers to expend resources to return the SC to normal (Tang, 2006).

### **Supply chain risk management**

*Supply chain risk management* (SCRM) alludes to the coordination resources and the collaboration of SC partners to ensure continuity and profitability. The RM literature suggests four SCRM strategies, avoidance, mitigation, transference, or acceptance (Piney, 2003). Avoidance argues for organizations to discontinue the use of risky practices. Mitigation suggests engaging in activities that reduce consequential effect. Practitioners employ transference by shifting risk and the resulting consequences to a third party, such as a vendor or insurer. Acceptance advocates for developing systems to absorb the consequences of SC disruption.

## **Warning capability**

*Warning capabilities* (WARN) refer to “interactions and coordination of SC resources to detect a pending or realized disruption and to subsequently disseminate pertinent information about the disruption to relevant entities within the SC” (Craighead et al., 2007, p. 146). The term detection represents an ability to recognize a hazard.

Organizations that detect SC disruptions before they occur have time to evaluate them and respond. Without detection, there is no signal indicating that a response is necessary.

The terms pending and realized illustrate that a disruption can take varied forms. A pending disruption is one that has not yet occurred. Here, warning indicators, such as a delayed shipment or poor quality raw materials, may indicate that a SC disruption is possible. Conversely, in situations such as earthquakes, disruptions can occur without warning. Therefore, identification occurs after a disruption happens. Within the business context, realized consequences include quality issues, unplanned outages, and delayed deliveries from suppliers.

Organizations must also “disseminate pertinent information about the disruption to relevant entities within the SC” (Craighead et al., 2007, p. 146). This reflects a firm’s INFOSHR and communication abilities. During a disruption, communication channels may break down or become inefficient. Therefore, redundant systems insure that communication is possible.



## **Recovery capability**

*Recovery capability* (RECOVER) refers to “interactions of SC entities and the corresponding coordination of SC resources to return the SC to a normal and planned level” (Craighead et al., 2007, p. 144). Organizations use pre-emptive recovery to initiate response efforts before an actual disruption occurs and reactive capabilities to respond after a SC disruption occurs. Normal and planned levels allude to a steady state of production or service.

### *Pre-emptive recovery*

When organizations identify a SC threat before its manifestation, they may be able to mitigate the threat. Mitigation refers to actions taken to reduce disruption consequences. The reduction potential depends on the type of disruption, consequences created, resources marshalled, and the amount of time until the disruption occurs.

By understanding the source of a risk, potential consequences, and the resources available, organizations can preemptively prepare for a SC disruption. The opportunity to mitigate the disruption effects increases if the warning window expands. The warning window represents the time between when practitioners acknowledge a SC threat and when the disruption actually occurs (Riley, Miller, & Sridharan, 2012).

### *Reactive recovery*

Practitioners should use *reactive recovery* capabilities after an actual SC disruption occurs. “These purposive interactions and coordination of resources allow

interventions to be designed and implemented to overcome the slowing or stoppage of planned product flow within the SC” (Craighead et al., 2007, p. 144). We argue that most organizations will attempt to reduce the amount of time associated with recovery efforts.

By reviewing the many characteristics of risk as they pertain to SC management and SCRM, we are able to ground our thinking as we develop new models, hypotheses, and measures. In section 3, we propose a model that links three antecedent competencies, to measures for warning and recovery capabilities, and organizational performance. We then develop new hypothesis framed by HRT thinking. Then in section 4, we test the validity and reliability of the two new RM measures along with existing measures for the antecedent competencies and organizational performance. The intent is to operationalize measures and a measurement instrument that researchers can use when investigating future SC and RM topics.

### **Proposed Model and Hypothesis Development**

Drawing on HRT, this research aims to show that behavior based RM techniques can mitigate risk with hospitals. To do so, we intend to illustrate how three antecedent competencies affect two RM capabilities and the organization’s business performance. We propose a conceptual model (Figure 1) based on the SC and RM literature and several qualitative interviews.

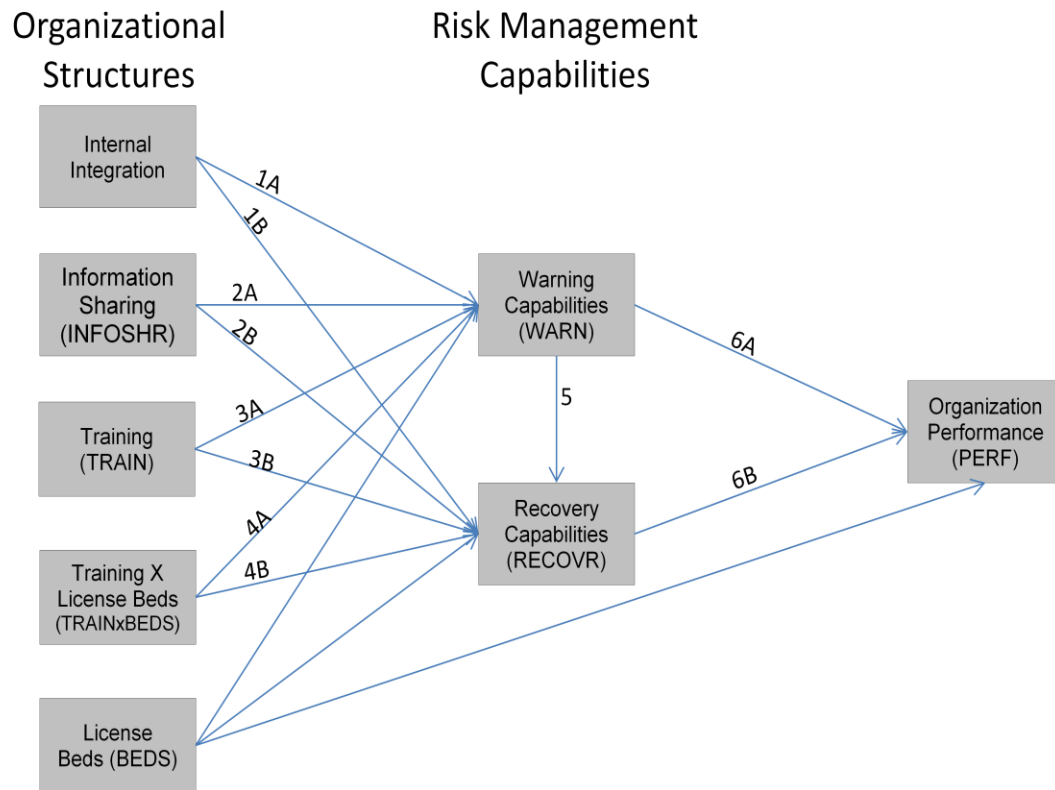


Figure 1: Proposed Model

### Theoretical model

The objective of this research is to validate measures of the WARN and RECOVR constructs. We use confirmatory factor analysis (CFA) to establish the instrument's unidimensionality and reliability along with the convergent and discriminant validity. To achieve this goal, we developed a structural model to define the relationships between three antecedent competencies and the proposed RM capabilities. To test the relationships, we collect and analyze survey data from U.S. hospitals.

Internal integration, TRAIN, and INFOSHR are structures that provide connectedness by influencing an organization's ability to align priorities and communicate those ideals. In the proposed model, we represent these organizational structures as antecedent competencies. Like Sinkula (1994), we argue that managers can manipulate these structures to create a positive change in behavior. This thinking complements HRT, which suggests that managers can manipulate competencies to affect an organization's ability to learn from mistakes and near misses (Weick et al., 1999).

We included the interaction TrainingXLicensed beds (TRAINxBEDS) to test the moderating effect of organization size. We believe organization size or hospital size is important to the study of training since larger organizations typically will have more employees who could benefit from additional formal training. Previous research supports our assumption about training and organization size (Frazis, Herz, & Horrigan, 1995). Additionally, OM researchers regularly use licensed beds to characterize hospital size (Goldstein & Naor, 2005; Tucker, 2004).

The WARN and RECOVR constructs represent organizational RM capabilities. Researchers have postulated that these RM capabilities moderate the severity of a SC disruption by lessening the effect of SC density, complexity, and node criticality (Craighead et al., 2007). We extend this thinking and suggest that both WARN and RECOVR positively affect organizational performance. Because these RM capabilities reduce the timing associated with detecting and responding to SC disruptions, we anticipate that organizations will be able to lessen the effect of an actual disruption. By

extension, we expect that improved responsiveness would decrease expenditures, improve profitability, and increase customer satisfaction levels.

We treated both *WARN* and *RECOVR* as intermediate outcomes while considering *organizational performance* as the final performance outcome. *WARN* serves as an intermediary between the antecedent capability and the organizations response and recovery capabilities. In this research, we tested the relationships among the antecedent competencies and *RECOVR*. We aimed to determine whether the relationships are direct, indirect (i.e., completely mediated by *WARN*), or both direct *and* indirect (i.e., partially mediated by *WARN*). Next, we put forth our research hypotheses.

### **Proposed relationships**

In the following section, we identify key terms used within the formal hypotheses. This includes definitions for three competencies, internal integration, information sharing, and training. Additionally, we give details to the two capability constructs, warning and recovery, and the moderating variable licensed beds.

### **Internal integration**

By definition, *internal integration* suggests that managers can unify processes and functions within an organization to accomplish higher-level goals and objectives (Germain & Iyer, 2006). In this research, SC functions such as procurement and logistics are able to internally integrate and support key hospital objectives. Key dimensions to this definition include coordination, collaboration, and interconnectedness.

### **Information sharing**

Li et al. (2005) defined INFOSHR as “the extent to which critical and proprietary information is communicated to one’s supply chain partner” (p. 621). As this research investigates internal connectedness, we seek to understand information sharing as data and knowledge, including proprietary information, is communicated between individuals and departments. We envision that people, processes, and systems help distribute information.

### **Training**

*Training* refers to the formal and informal processes of teaching practitioners within an organization job-related skills and knowledge (Kaynak, 2002). Training may be necessary for specific tasks or functions, general knowledge, certification, or as a refresher concerning a previously studied topic.

### **Licensed beds**

The number of *licensed beds* refers to “the maximum number of beds for which a hospital holds a license to operate (ahrq.gov). While the term alludes to a maximum number, some hospitals do not operate to this number.

### **Formal hypotheses: Relationships with SCRM capabilities**

Below are the formal hypotheses of this study. We proposed each relationship a-priori and under the purview of HRT. For each competency-capability linkage, we offer two direct relationships and one mediated relationship that work through the intermediary warning capabilities.

#### **Relationship between internal integration and the organizational SCRM capabilities (H1A-C)**

Experts agree that the first principle of managing risk is to organize one's affairs before requiring others to do so (Handfield & Nichols, 1999; Kleindorfer & Saad, 2005; Swink, Narasimhan, & Kim, 2002). Thus, organizations should integrate their own SC functions before integrating externally. Internal integration refers to practices that enable and encourage interaction between internal processes and partners. From the HRT perspective, internal integration is akin to structural coupling, a mechanism that enables dependence between internal functions (Smart et al., 2003). In our investigation, internal integration details the extent to which organizations collaborate across internal boundaries to provide a refined customer experience (Chen & Paulraj, 2004). Integrating activities include cross-functional cooperation (Ballou, Gilbert, & Mukherjee, 2000) and information system integration (Sahin & Robinson, 2005). If managers develop this competency properly, internal integration reduces information uncertainty and equivocality (Koufteros, Vonderembse, & Jayaram, 2005) and improves practitioner

decision making. Without internal integration, practitioners may form functional silos, which optimize divisional processes rather than organization.

### **Warning capability**

Internal integration also empowers employees without direct supervision to interpret and respond to SC threats. Stated differently, internal integration should also speak to the willingness to cooperate, not just the requirement of compliance (Chen & Paulraj, 2004). HRT theorists call this mindfulness and use this term to describe employees that make operational decisions without formal structure or authority (Weick & Sutcliffe, 2001, 2006). Jun, Qiuzhen, and Qingguo (2011) found that internal integration enhances communication between team members. The ability to communicate quickly and clearly is important for practitioners within complex organizations. Otherwise, misinformation leads to sub-optimal solutions. Thus, we hypothesized:

*H1A-Organizations with higher levels of internal integration competence will have higher warning capability levels.*

### **Recovery capability**

As an antecedent to RECOVER, internal integration enables high information processing capabilities and allows organizations to address risk systematically (Jun et al., 2011). Preemptively, managers employ information from internally integrated systems and processes to position resources. Rapid deployment of resources and personnel improves the opportunity to lessen the effect of pending SC disruptions. Examples of



resource placement include sand bags and storm shutters deployed before a flood or hurricane. When positioned, these resources enable organizations to minimize SC damage.

Internal integration also allows organizations to respond to disruptions after they occur. Emergency command centers and deployment support systems are examples of internal integration mechanisms designed specifically for reactive RM activities. Command centers enable decision makers to centralize information about disparate events and make decisions about response efforts and resource placement. Managers can deploy disaster recovery teams and activate redundant systems to lessen consequential effect. Ad-hoc committees and project managers enable cross-functional integration and combat compartmentalization within organizations (Germain & Droge, 1997). Hence, internal integration should enable response efforts. Leveraging this rationale, we developed the following hypothesis:

*H1B-Organizations with higher internal integration competence levels will have higher recovery capability levels.*

### **Mediated relationship**

We also hypothesized a mediated relationship between internal integration and RECOVR, where WARN serves as an intermediate step. See Figure 2. Using the Craighead et al.'s (2007) definition, WARN allows for the “coordination of supply chain resources to detect a pending or realized disruption” (p 146). Hence, organizations use their scanning abilities to accumulate information about SC threats and disruptions. With

this information, managers can properly integrate systems and position response teams and resources to hasten recovery efforts. In this capacity, WARN enhances organizational connectedness, which enables response and recovery capabilities. Leveraging this logic, we offer the following:

*H1C- Warning capability mediates the relationship between internal integration and recovery capability.*

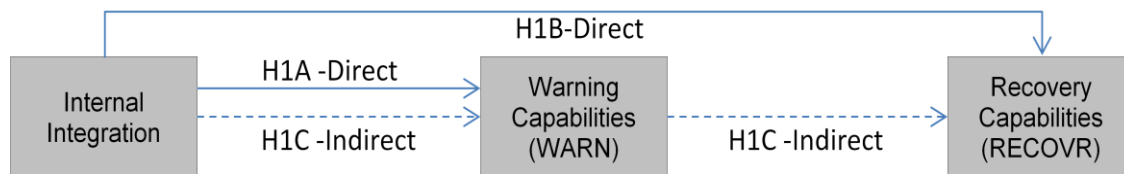


Figure 2: Warning mediates the internal integration-recovery capability relationship

## Relationship between Information Sharing and the Organizational SCRM Capabilities (H2A-C)

We define INFOSHR as the act of and the willingness to make information available to other employees, departments, and partners. Research suggests that organizations embrace this competence when practitioners exhibit a willingness to share information (Spekman, Kamauff, & Myhr, 1998). Willingness to share information alludes to an organization's commitment and the level of trust associated with actually sharing information. In this research, we extend current thinking and investigate INFOSHR from an intra-organizational perspective. Therefore, INFOSHR enables employees within an organization to heedfully interrelate and emphasize alertness (Smart et al., 2003; Weick & Roberts, 1993).

### **Warning capability**

Evidence demonstrates that INFOSHR amongst SC participants is essential for organizations that want to identify and prepare for vulnerabilities (Kleindorfer & Saad, 2005). This occurs as INFOSHR allows practitioners to collect information from multiple sources and then engage in coordinated decision-making efforts (Sahin & Robinson, 2005).

We put forth that INFOSHR improves WARN and creates a state of alertness when processes allow employees to share data about threats throughout the organization. After practitioners identify a threat, INFOSHR permits managers to communicate response strategies. Cachon and Fisher (2000) supported this claim and showed how INFOSHR allows organizations to flow goods through the SC more quickly and evenly. Further, INFOSHR enables the interdependence and coupling of internal functions. Therefore, this structural mechanism is an important connectedness practice, which is common in highly reliable organization (Smart et al., 2003). Thus, we offer the following:

*H2A-Organizations with higher levels of information sharing competence will have higher warning capability levels.*

### **Recovery capability**

Organizations should also use INFOSHR practices to develop their RECOVER by providing details on how to respond to actual SC disruptions. Practitioners who share

information about disruption consequences are able to prescribe specific countermeasures. Managers can first direct responders towards stabilization efforts, shutting down affected systems or mitigation practices designed to prevent further damage (Sheffi & Rice, 2005). We hypothesize that customized response tactics are more appropriate compared to generic efforts, as they enable faster recovery and help minimize SC damage.

We argue that when organizations identify threats preemptively, practitioners can share information to develop and deploy an appropriate mitigation strategy. For instance, in 2002, Dell's management was evaluating the possibility that 29 West Coast ports would close due to a pending dockworker strike. Before the labor strike occurred, managers moved raw materials from Asia to US via airfreight. In this case, Dell uses information to plan and avoid a SC disruption due to the strike (Breen, 2004).

Additionally, organizations may use the INFOSHR competency also when reactively responding to a SC disruption. Here, INFOSHR improves practitioners' decision-making processes. For example, if an organization experiences a quality issue, shared data about the extent and expected duration of the disruption provides information on how to speed recovery efforts. This follows the HRT premise that employees should gather information from multiple sources when making response decisions. From this perspective, we offer the following hypothesis:

*H2B-Organizations with higher levels of information sharing competence will have higher recovery capability levels.*

### Mediated relationship

We further hypothesized that WARN mediates the INFOSHR – RECOVER relationship. See Figure 3 for an illustration. WARN, as an intermediate step, bolsters the INFOSHR competency by enhancing communication abilities. We believe that response agents benefit when practitioners exploit their communication abilities and share strategic, tactical, and operational information (Bharosa, Van Zanten, Zuurmond, & Appelman, 2009). Stated differently, practitioners responsible for recovery efforts need to share information, including information gathered during the WARN processes, in order to prescribe context specific response tactics. Hence, we predict a mediated effect:

*H2C- Warning capability mediates the relationship between information sharing and recovery capability.*

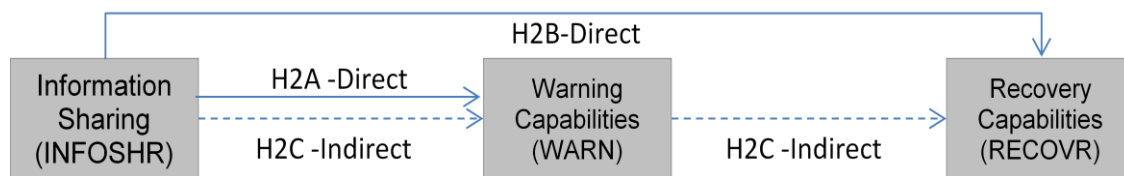


Figure 3: Warning mediates the information sharing-recovery capability relationship.

### Relationship between Training and the Organizational SCRM Capabilities (H3A-C)

Practitioners draw on the TRAIN competency to learn about disruptions and appropriate management tactics. Research indicates that TRAIN enables practitioners to convert a topic's conceptual understanding into actual practice. Therefore, TRAIN refers to formal activities, which facilitate learning (McGehee & Thayer, 1961). From a HRT

perspective, organizations derive new knowledge from formal TRAIN activities and informal socialization activities.

### **Warning capability**

When TRAIN levels are low, organizations are passive to uncertainty and “accept whatever information the environment gives them” (Daft & Weick, 1984, p 288).

Practitioners feel immune to threats or believe that alternative mechanisms, such as SC partners, enable them to mitigate the disruption consequences. Active organizations, in contrast, aspire to protect themselves from uncertainty. Thus, active organizations expect disruptions to occur and embrace TRAIN as a method to prepare for the inevitable. By doing so, managers assume that employees can mitigate uncertainty with detection practices that reduce the probability of occurrence and response tactics that lessen the disruption’s effect and recovery time.

In the RM context, TRAIN is important both before and after a disruption occurs. Classroom instruction, practice, and exercising typically occur before a disruption (Ford & Schmidt, 2000). This pre-emptive TRAIN allows employees to understand the utility and limitations of existing RM tactics. This occurs as TRAIN provides understanding and creates a permanent change in knowledge and attitude (Ford & Schmidt, 2000). Hence, we hypothesize the following relationship:

*H3A- Organizations with higher training competence levels will have higher warning capability levels.*

### **Recovery capability**

RM experts also suggest that TRAIN enables practitioners to respond during periods of uncertainty, such as a SC disruption (Ritchie & Brindley, 2007). However, we recognize that TRAIN conditions can vary significantly from those experienced during an actual disruption. Therefore, we agree with previous research and suggest that post-disruption TRAIN is also necessary (Ford & Schmidt, 2000). Practitioners develop detailed response procedures to address disruption circumstances that have already occurred. Automotive recalls are actions taken to repair or remove products from the marketplace after a disruption has occurred. Once a manufacturer identifies a recall, employees respond by completing repairs or replacing the defective component. The TRAIN procedures instruct employees on how to correct prescribed problems. This leads to the following hypothesize:

*H3B- Organizations with higher training competence levels will have higher recovery capability levels.*

### **Mediated relationship**

We also envision that the WARN construct affects the linkage between TRAIN and RECOVR. Figure 4 depicts the mediated model. When responding to a SC disruption, practitioners should apply information about the type of threat. This includes information obtained from scanning activities, a dimension of the WARN construct. In this perspective, practitioners seek out signs indicating a pending or actual SC disruption.

Warning details should inform the organization on how to best respond to and/or mitigate SC threats. For instance, Oloruntoba (2005) argued that public officials need information pertaining to tsunamis (or other natural disasters) to raise awareness and improve logistics coordination. When warning agents communicate information pertaining to the tsunami's impact zones ahead of time, officials can preemptively respond by evacuating the population or prepositioning resources. Reactively, WARN information should provide details on how to minimize the disruption's influence and/or shorten recovery times associated with SC disruptions that has already happened. For example, Zhang, Chai, Yang, and Weng (2011) found that warning information improves the organizations ability to execute recalls within a food SC. Specifically, traceability systems use warning information that enable managers to “effectively and speedily determine material or production stages having problems” (Zhang et al., 2011, p. 2507). On this basis, we suggest the following mediated relationship.

*H3C- Warning capability mediates the relationship between training and recovery capability.*

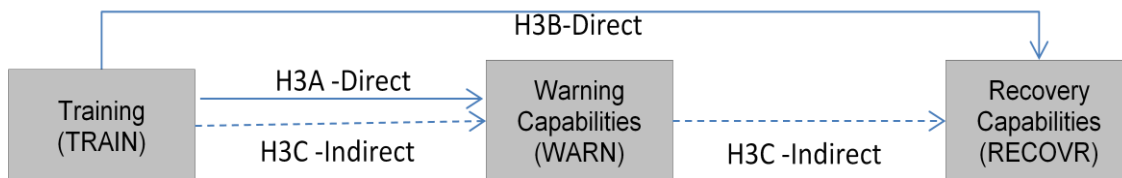


Figure 4: Warning mediates the training-recovery capability relationship.



#### **Moderating relationship of organization size on the training competence (H4A-C)**

The human resource literature consistently confirms that firm or organization size moderates the effects of training on performance (e.g., Guest 1997; Guest, Mitchie, Conway, & Sheeham 2003; Combs, Liu, Hall, & Ketchen 2006; Lee 2012). Several theories offer explanations as to why this interaction exists; however, a full review of these perspectives is out of scope for this research. While this stream of literature about potential interactions between TRAIN and organization size is informative, most studies adopt a human resources perspective.

When reviewing the SC and SCR literature, we found that only few researchers have investigated the abovementioned interaction. Manuj and Mentzer (2008) identified this gap and encouraged researchers to test moderating (and mediating) effects in the SCRM context. Thus, we sought to understand whether organization size moderates the relationship between TRAIN and the two RM capabilities and how.

We hypothesize a positive relationship between TRAIN-WARN (H3A) and TRAIN-RECOVR (H3B). Using HRT as our theoretical frame, we speculate that TRAIN activities, such as simulation and practice, prepare the organization for SC disruption. In essence, training allows practitioners to think about potential threats and consequences before they occur. This happens as managers establish norms, enable self-direction, and motivate employees to act (Batt & Moynihan 2006). We believe that these norms and the motivation to act are characteristics of mindful employees who operate complex systems.

In the healthcare context, organization size relates to the number of licensed beds (BEDS) (Kaczmarek et al., 1991; Kaczmarek et al., 1992). We suppose that as BEDS increases, so does the need for training (TRAINxBEDS). Stated differently, TRAIN needs increase as managers bring more service products into the hospital. However, we note that training effectiveness may diminish as organization size grows, because it would become difficult to deliver a consistent level of training. Based on this logic, we hypothesized the following moderated relationships: See Figure 5 for an illustration of the moderated relationships for hypotheses H4A and H4B.

*H4A – The effect of training on warning capability diminishes as BEDS increases (TRAINxBEDS –WARN).*

*H4B– The effect of training on recovery capability diminishes as BEDS increases (TRAINxBEDS –RECOVR).*

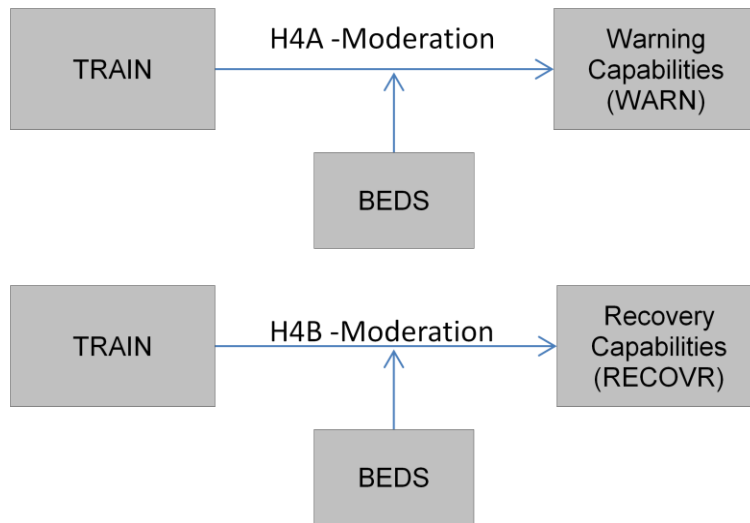


Figure 5: BED moderates the TRAIN-WARN and TRAIN-RECOVR relationships

We also believe that WARN moderates the mediated relationship between TRAINxBEDS and RECOVER. See Figure 6 for an illustration of mediated-moderation. Here WARN serves as an intermediate step between the antecedent competency and the capability construct.

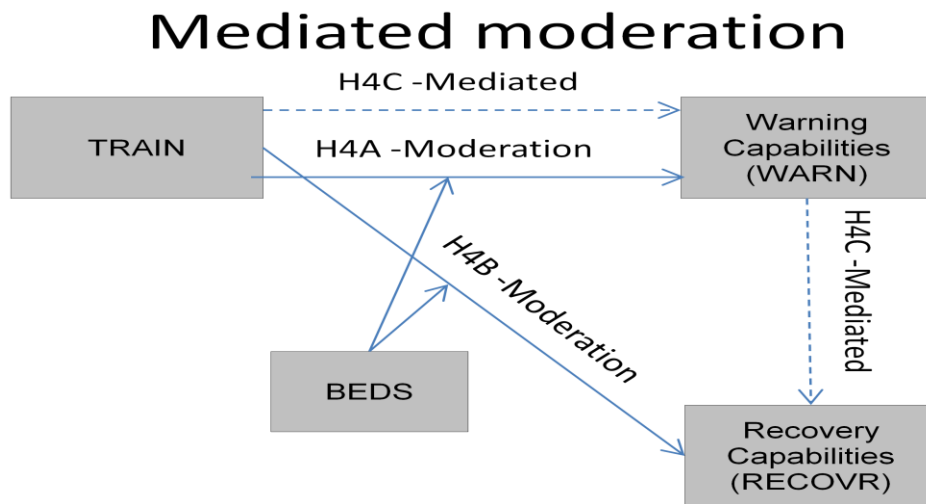


Figure 6: WARN mediates the TRAINxBEDS-RECOVER relationship.

We suggest that the TRAINxBED –RECOVER relationship improves when WARN is included in the analysis. As BEDS increases, so does the number of practitioners available to scan for an identify SC threats. When practitioners identify a SC threat, they can provide response agents with information, which may help reduce the probability of a disruption. Additionally, practitioners responsible for recovery activities may glean information from WARN practices and subvert consequential effects or improve recovery times by suggesting methods that can be used to respond during

disruption. We believe some suggestions will stem from TRAIN and practice activities, which we consider a key WARN antecedent. Using this logic, we offer the following:

*H4C- Warning capability positively mediates the moderated relationship between TRAINxBED and recovery capability.*

#### **Relationship between warning and recovery capabilities (H5)**

If WARN is properly employed, organizations have information and time to determine an appropriate course of action. Thus, when practitioners identify a threat before it occurs, the organization may be able to minimize or even avoid a SC disruption. In the case of a delayed shipment of raw materials, an alternative vendor may be able to supply replacement product. When disruption is unavoidable, WARN capabilities allow managers to muster resources and proactively mitigate consequences. For example, when experts predict a hurricane, large home improvement retailers preposition inventory to suppress the storms effect with storm shutters and speed recovery efforts with cleaning supplies (Lodree, Ballard, & Song, 2012). Therefore, when organizations have high levels of warning capabilities, they may be able to jumpstart recovery efforts and reduce the consequences and recovery time associated with a disruption. Hence, we hypothesize the following:

*H5-Organizations with high warning capability levels will have high recovery capability levels.*

### **Relationship between the RM capabilities and organizational performance (H1A-C)**

We evaluated performance with three perceptual measures: operating cost, out-of-stocks, and service quality. Most practitioners consider out-of stocks and operating costs as an indicator of business success (Challis & Samson 1996). In addition, researchers use service quality as a measure of success within the operations management literature when studying hospital environments (Marley, Collier, & Goldstein 2004).

### **Relationship between warning capabilities and organizational performance**

Organizations with strong WARN should be able to scan the SC horizon and identify threats before they happen. Peck (2005), for example, illustrated how news service scanning activities enabled German beverage manufactures and suppliers to avoid disruption associated with environmental legislation. Early identification provides time in which the organization can reconfigure tactics and position resources to thwart pending disruptions.

Further, we believe that once an organization identifies a threat, managers can use their communication skills to disseminate information about threats to partners. When organizations enhance their communication abilities, it improves understanding, builds trust, increases confidence, and reduces the risk exposure (Ritchie & Brindley 2000). Thus, when practitioners communicate information about risk sources and potential consequences properly, they are able to mitigate the disruptions effects, minimize SC downtime, and focus on long-term organizational goals, such as safety and profitability.

Lastly, in certain situations, practitioners will identify a SC disruption only after it occurs. Both manmade and natural disasters can occur with no warning. Practitioners in addition, may miss warning signs altogether. When such disruptions occur, organizations must work quickly to understand the source and resulting consequences to help managers develop appropriate response tactics.

When organizations have time and are able to communicate information about threats, they should be able to reduce the probability, effect, and recovery times of a SC disruption. Essentially, managers are removing the uncertainty associated with their operating environment by lowering the overall level of exposure to disruption. With less exposure resulting from better WARN, organizations should be able to improve organizational performance. Hence, we propose the following hypothesis concerning warning capabilities:

*H6A-Organizations with higher warning capability levels will have higher performance levels.*

Besides the direct effect between WARN and PERF, we envision that RECOVER capabilities mediate the relationship and creates a positive indirect linkage. Figure 7 illustrates this effect. The indirect effect suggests that an organization has both strong warning and recovery capabilities. However, if only the indirect linkage is present, the organization needs both RM capabilities to affect positively the outcome construct PERF. Additionally, the direct effects are present between WARN and PERF, then a partially mediated relationship exists. We initially hypothesized a direct relationship between

WARN and PERF (H6A); however, we also suggest that a partially mediated linkage through RECOVR (H6B). This occurs as practitioner use information gleaned from WARN practices to enhance the organization's response capabilities, which improves the level of PERF. From the HRT perspective, highly reliable organizations develop both WARN and RECOVR capabilities and cooperatively share information regarding the two functions. This line of reasoning allows us to hypothesize the following:

*H6B- Recovery capability partially mediates the relationship between warning capability and organizational performance.*

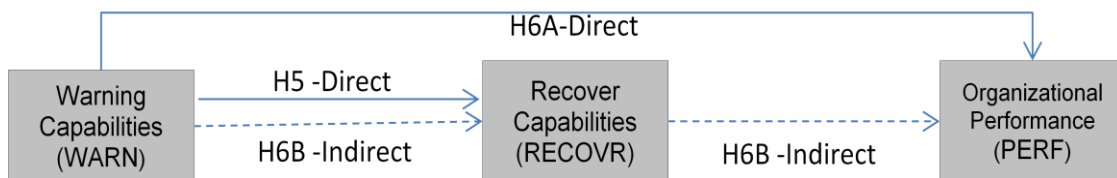


Figure 7: Recovery mediates the warning capability-performance relationship.

### **Relationship between recovery capabilities and organizational performance**

Practitioners should use RECOVR to deploy resources and develop tactics to mitigate the effects of a SC disruption. Highly reliable organizations are able to learn from environmental queues and adapt to the changing business environment. To this end, organizations can build and defend their competitive advantage by developing recovery capabilities.

Pre-emptive recovery allows organizations to reduce the probability of occurrence and lessen the actual influence. Once an organization understands how a threat will manifest, managers can reconfigure resources and tactics. This allows organizations to

either avoid the threat prior to disruption or gather resources for response tactics that address the consequences that emanate from a disruption.

Reactive RECOVR enables organizations to react to disruptions. The ability to react quickly is important when a disruption event offers no warning or when practitioners are unable to foresee an occurrence. During reactive periods, practitioners evaluate how a threat has manifested and then marshals the appropriate resources to counteract consequences. For example, in 1989, work crews repaired the eastern span of the Bay Bridge after the Loma Prieta earthquake damaged it just over a month earlier (Citizendia.org). California department of transportation (CDOT) executives worked to determine the quickest way to reopen the earthquake-damaged bridge that transported thousands of commuters daily. In this case, no one was able to stop the disruption from happening. Therefore, the best solution was to react quickly and reduce the time the bridge was unavailable. Using large financial incentives, the CDOT encouraged workers to repair the bridge. The bridge reopened on November 18, 1989, one month and one day after the earthquake. From this position, we offer the following hypothesis.

*H6C-Organizations with higher levels of recovery capabilities will have higher performance levels.*



In Table 1, we summarize the hypotheses used within this research. We then precede the methodology section and describe procedures used to operationalize the various constructs. Within this section, we discuss specifically the warning and recovery capability constructs, as these are paramount to our research. Finally, we review our qualitative and quantitative testing procedures.

Item	Hypothesis
H1A	Organizations with higher levels of internal integration competence will have higher warning capability levels
H1B	Organizations with higher internal integration competence levels will have higher recovery capability levels
H1C	Warning capability mediates the relationship between internal integration and recovery capability
H2A	Organizations with higher levels of information sharing competence will have higher warning capability levels
H2B	Organizations with higher levels of information sharing competence will have higher recovery capability levels
H2C	Warning capability mediates the relationship between information sharing and recovery capability
H3A	Organizations with higher training competence levels will have higher warning capability levels
H3B	Organizations with higher training competence levels will have higher recovery capability levels
H3C	Warning capability mediates the relationship between training and recovery capability.
H4A	The effect of training on warning capability diminishes as BEDS increases (TRAINxBEDS –WARN).
H4B	The effect of training on recovery capability diminishes as BEDS increases (TRAINxBEDS –RECOVR).
H4C	Warning capability positively mediates the moderated relationship between TRAINxBED and recovery capability
H5	Organizations with high warning capability levels will have high recovery capability levels.
H6A	Organizations with higher warning capability levels will have higher performance levels.
H6B	Recovery capability partially mediates the relationship between warning capability and organizational performance.
H6C	Organizations with higher levels of recovery capabilities will have higher performance levels.

Table 1: Summary of Hypotheses

### **Instrument Development**

We put to use Noar's (2003) approach to develop the warning and recovery measures. Initially, we reviewed the literature to identify potential definitions and measurement items. We also reviewed tangential literature, such as business continuity management, crisis management, and SC complexity, to identify complementary operationalizations. See Table 2 for a list of constructs, dimensions and originating authors.

We employed multiple iterations of item-to-construct sorting procedures (Q-sort) to purify questions and definitions. Utilizing several samples of convenience, undergraduate students, graduate students, and industry experts matched measurement items with construct definitions (McKeown & Thomas, 1988). The Q-sorting process allowed us to refine measurement items and the accompanying definitions by assessing the face validity, inter-rater reliability, and construct validity (Menor & Roth, 2007).

For internal integration and TRAIN, the literature provided acceptable starting points. Few words were adapted during refinement process. For INFOSHR, we adapted measures from Li, Rao, Ragu-Nathan and Ragu-Nathan (2005). However, during the Q-sort process, many respondents failed to match INFOSHR questions to the construct definitions provided. Therefore, we further adapted questions included in the final survey instrument.

Construct	Dimension	Authors
Internal Integration	Integration dimensions of design knowledge intensity	Germain, Dröge and Christensen, 2001
Training	Statistical training and training resources	Saraph, Benson, and Schroeder, 1989;
	Statistical training and training resources	Forker, 1997;
	Cross training	Ahmad and Schroeder 2003;
Information Sharing	Exchanging information	Li, Rao, Ragu-Nathan, and Ragu-Nathan, 2005
Warning Capabilities	Identify and communicate	Craighead et al., 2007;
	Early and late warning	Schmeidl and Jenkins, 1998;
	Discovery	Hays and Hill, 2000;
	Monitoring	Grover and Malhotra, 2003;
	Communication	Chen and Paulraj, 2004;
	Communication	Chen, Paulraj, and Lado, 2004;
	Identify/mitigate threats in advance	Zsidisin and Ritchie, 2009
Recovery Capabilities	Proactive and reactive response	Craighead et al., 2007;
	Engaging responses, assets and capabilities	Olavarrieta and Ellinger, 1997
	Response agility	Schmeidl and Jenkins, 1998
	Recovery expectations and performance	McCollough, Berry, and Yadav, 2000;
	Early involvement	Koufteros, Vonderembse, and Doll, 2002;
	Practice recovery behaviors	de Jong and de Ruyter, 2004;
	Scenario planning and simulations	Smith, 2011

Table 2: Constructs, dimensions, and originating authors.

### Warning and recovery capabilities

For the two organizational RM measures, warning and recovery capability, we adapted the construct definitions from Craighead et al. (2007). Initially they proposed the two measures in the risk mitigation context. However, as far as we can discern, Craighead and colleagues or other authors did not operationalize these constructs within literature. For WARN, we developed an exhaustive list of potential measurement questions from the RM, scanning, sense making, and communication literature. For RECOVR, we adapted measures from business continuity, SC agility, and the crisis management literature. We utilized these literature streams to insure coverage of the construct domain and centroid

(Little, Lindenberger, & Nesselroade, 1999). See Appendix A for item correlations. See survey questions 7-12 in appendix B.

### **Internal integration**

For questions about internal integration, we adapted measures from Germain, Dröge, and Christensen (2001). Their research studied cross-functional integration to determine how organizations collect, process, and integrate design knowledge. Like Germain et al. (2001), we envisioned that connectivity and coupling mechanisms are necessary to integrate different SC functions. Therefore, we developed our internal integration questions to address both SC integration activities and mechanisms that encourage connectivity. See questions 1-3 in appendix B.

### **Information sharing**

We started with the INFOSHR measures proposed by Li et al. (2005) and then adapted them to address INFOSHR from an internal perspective. Their questions addressed the external information exchange. We amended questions so they would tap INFOSHR concepts from both a management and practitioners' perspective. In addition, we also tried to gauge the importance of internal INFOSHR. Consequently, we developed 10 questions used within Q-sort procedures. These sorting exercises enabled us to select three appropriate questions. See questions 16-18 in appendix B.

## **Training**

Questions pertaining to TRAIN were adapted from Saraph, Benson, and Schroeder (1989), Forker (1997), and Ahmad and Schroeder (2003). We amended the Saraph et al. (1989) and Forker (1997) questions to address organization wide TRAIN initiatives. We also drew statistical TRAIN questions from these articles; however, the Q-sorting results encouraged us to drop these questions from the final survey instrument. Lastly, we developed several questions that addressed cross-training practices. We adapted these questions from measures designed to tap multiple functions of TRAIN (Ahmad & Schroeder, 2003). We believe that both TRAIN and cross-training principles are important within an organization supported by a complex SC. See questions 13-15 as described in appendix B.

We reviewed several drafts of our proposed model with academic and practitioner experts. They provided qualitative feedback on both the antecedent competencies and the proposed RM capabilities. Appendix B lists the final survey questions.

## **Research Methodology**

### **Expert review**

Once we created an initial set of construct definitions and measurement items, we reviewed the concepts, the proposed model, and the survey instrument with seven practitioners familiar with SC and RM concepts. This allowed us to establish the construct or face validity (Anastasi, 1988). Four of the interviewees worked within the healthcare industry. This includes a procurement director, hospital administrator, retired

risk executive, and a senior vice president of a non-profit hospital group. The primary investigator also conducted three interviews with non-hospital procurement experts to confirm the generalizability of the concepts. Two experts worked for a large retail chain while the other worked as a procurement director for a large public university.

### **Unit of analysis**

The unit of analysis is the business unit within a hospital. We selected hospital materials managers and directors as they are likely familiar with the antecedent competencies and the RM capabilities included in the study. After reviewing the concepts with interviewees, we believe the target respondents have sufficient knowledge to complete the survey. Thus, we suggest that data collected will provide enough variance to test the proposed relationships.

### **Data collection**

We collected pilot data from an evening Master of Business Administration (MBA) operations management class. These respondents had professional work experience and had knowledge of procurement and operations activities. The MBA instructor offered respondents extra credit to complete the pilot survey. From this sample, we were able to use 54 of 57 responses. We discarded three responses due to large amount of missing data.

We then collected pre-test data from 49 hospital procurement managers and directors in July and August 2012. Using an email survey (Qualtrics.com), we collected

data in two phases. Initially, a vice president at a non-profit hospital organization (name of organization is withheld for confidentiality) sent the survey to 150 procurement directors. We were able to use 16 of the completed responses. Second, we purchased an email list of 839 potential respondents from SK&A (SKA.COM). We received 33 completed responses. In this case, we sent each respondent a \$25 gift card. The data from the pilot and pretest informed us about how to adjust the final survey instrument.

We conducted the full survey in the winter of 2012/2013 in three phases. Initially, we distributed the questionnaire to customers of a non-profit group purchasing organization (GPO) (name of organization is withheld for confidentiality). The GPO sent out nine hundred and thirty surveys via email without incentives. After reviewing 72 potential responses, we discarded 10 due to major omissions. Therefore, we used 62 or 6.7% of the responses in the final analysis.

During the second phase, we purchased an email list from SK&A (SKA.COM). They emailed the survey to 1,600 procurement managers and directors working in US hospitals. With a \$10 gift card as incentive, we received responses from 5.5% of the respondents. After a review, we were able to keep 88 of the completed surveys.

Finally, we mailed a paper survey to approximately 297 hospitals located throughout the US. In this case, we gave potential respondents a one-dollar bill as an incentive. We used names and addresses as listed on <http://www.hospitalvendorcredentialing.com>. Twelve surveys were returned due to an incorrect address or because hospital policy forbid employees from participating in



surveys. Therefore, out of 287 eligible surveys, we received 65 completed surveys representing a 22.1% response rate.

Using all three methods, we collected 215 total responses reflecting a response rate of 7.6%. Table 3 identifies the method used and final response rates. While these response rates may be slightly lower than those of other surveys within OM, we believe the sample is adequate, as there is limited number of hospitals within the US. According to the American Hospital Association, there are 5,724 hospitals in the US (AHA.ORG).

Method	Not			
	Sent	valid	Usable	%
GPO	937	10	62	6.70%
SKA	1600	0	88	5.50%
Mail	297	12	63	22.10%
Total	2827	22	213	7.60%

Table 3: Method Response Rates

### Sample size

Following Bartlett, Kotrlik, and Higgins (2001) we calculated the required minimum sample size for this investigation. Based on the Bartlett et al.'s equation, three factors are necessary to compute the minimum sample size: alpha level ( $\alpha$ ), an estimate of the population's standard deviation ( $s$ ), and an acceptable margin of error for the estimated mean ( $d$ ). This allows researchers to account conservatively for risk. Hence, we use an alpha level of 0.01. For standard deviation, Bartlett et al. (2001) suggested an

estimate of 1.167. This estimate is appropriate for a 7-point Likert scale. Third, we estimated 0.21 as an acceptable margin of error. This number is the product of the number of options within our scale and the margin of error a researcher is willing to accept. When using the three input variables in the Bartlett et al.s' equation, we calculated  $n_o$  to be 204.925.

$$n_o = \frac{(t)^2 * (s)^2}{(d)^2} = \frac{(2.576)^2 * (1.167)^2}{(7*0.03)^2} = 204.925 \text{ or approximately 205 respondents.}$$

Following Cochran (1977), we adjusted the above equation to account for the small population size. With 5,724 hospitals in the U.S. (AHA.com), we corrected the minimum required sample size.

$$n = \frac{n_o}{(1 + \frac{n_o}{Population})} = \frac{204.925}{(1 + \frac{204.925}{5724})} = 197.842 \text{ or approximately 198 respondents. With 215}$$

responses, we had acceptable amount of data to analyze using the structural equation modeling software EQS 6.2.

## Missing data

We excluded the control variables from the missing data analysis, since we replaced missing control variables with data from [hospitalvendorcredentialing.com](http://hospitalvendorcredentialing.com) (2013). For the remaining variables, we used EQS version 6.2 to impute missing data. Out of 3,824 response variables, only 26 were missing. Since this accounted for less than 1%, we tested the data to determine if it was missing completely at random (MCAR). Using Little's MCAR test, we found the missing variables to be MCAR (P=0.520). We

then used expectation-maximization (EM) imputation to estimate the missing variables (Allison, 2003).

### **Preliminary analysis**

We conducted a preliminary analysis to test for outliers, influential responses, skewness, kurtosis, and inappropriate responses (Tabachnick & Fidell, 2007). Specifically, we tested for univariate outliers by examining the standardized residuals as well as minimum and maximum values. See Table 4 for descriptive statistics. We used EM imputation to reproduce missing data points. We rounded a few imputed data up to the minimum of 1.0 or down to the maximum of 7.0. Two data points exceeded the 7.0 maximum by less than 0.2 points and 1 data point was below the 1.0 minimum by less than 0.1 points. The only exceptions to the minimum and maximum rules described above are the four control variables. Both university affiliated (UNIV) and teaching facility (TEACH) are dichotomous, hospital type (TYPE) was on a 4 point scale (1.0-4.0), and hospital class (CLASS) was on a 8 point scale (1.0-8.0). None of the control variables need to rounded.

NAME	CASES	MEAN	StdDev	Min	Max	Range	Skewness	Kurtosis
Internal integration 1	215	5.17	1.35	1.00	7.00	6.00	(1.00)	1.04
Internal integration 2	215	4.91	1.31	1.00	7.00	6.00	(0.85)	0.39
Internal integration 3	215	4.51	1.60	1.00	7.00	6.00	(0.54)	(0.52)
INFORSHR 1	215	5.68	1.21	1.00	7.00	6.00	(1.30)	2.01
INFORSHR 2	215	5.59	1.39	1.00	7.00	6.00	(1.30)	1.41
INFORSHR 3	215	5.73	1.25	1.00	7.00	6.00	(1.41)	2.28
TRAIN 1	215	5.05	1.45	1.00	7.00	6.00	(0.82)	0.24
TRAIN 2	215	5.42	1.35	1.00	7.00	6.00	(1.03)	0.78
TRAIN 3	215	5.19	1.37	1.00	7.00	6.00	(0.99)	0.66
WARN1	215	5.54	1.16	1.00	7.00	6.00	(1.36)	2.85
WARN2	215	5.58	1.27	1.00	7.00	6.00	(1.51)	2.74
WARN3	215	5.35	1.51	1.00	7.00	6.00	(1.19)	1.05
RECOVR1	215	5.88	1.14	1.00	7.00	6.00	(1.55)	3.82
RECOVR2	215	5.96	1.12	1.00	7.00	6.00	(1.86)	5.50
RECOVR3	215	5.78	1.28	1.00	7.00	6.00	(1.53)	2.74
PERF1	215	5.01	1.33	1.00	7.00	6.00	(1.09)	1.05
PERF2	215	5.78	1.23	1.00	7.00	6.00	(1.82)	4.07
PERF3	215	5.83	1.20	1.00	7.00	6.00	(1.97)	5.11
BED	215	3.05	2.10	1.00	7.00	6.00	0.78	(0.74)
UNIV	215	1.74	0.43	1.00	2.00	1.00	(1.12)	(0.72)
TEACH	215	1.60	0.48	1.00	2.00	1.00	(0.42)	(1.79)
TYPE	215	1.33	0.64	1.00	4.00	3.00	2.56	6.69
CLASS	215	2.50	1.13	1.00	8.00	7.00	2.27	7.31

Table 4: Descriptive Statistics: Before transformation procedures

For multivariate outliers, we calculated Mahalanobis distances, DFBETAs, and DFIT values. Response #135 exceeded the Mahalanobis distances, DFBETAs, and DFIT cutoffs suggested by SC literature. After review, we retained the observation response, as it only marginally exceeded the calculated cutoff values.

We also used Mardia's coefficient to identify observations that exhibit excessive multivariate kurtosis (Mardia, 1976). Three participants, #89, #106, and #123, had highly unusual response patterns resulting in extreme values, as measured by the Mardia coefficient. We removed these participants from further analysis. This left us with 212 observations for the final analysis. The corresponding normalized estimate for the Mardia coefficient was 32.2574.

Further, we identified four variables, PERF2, PERF3, RECOVR1, and RECOVR 2 that were highly kurtotic. Using PERF2 as an example, 195 of 214 respondents answered with a 5.0, 6.0, or 7.0. (See Figure 8) Conversely, only 19 respondents answered with a Likert value of 1.0 to 4.0. While no absolute kurtosis figure indicates non-normality, Bentler (1995) suggested that large kurtosis values of + three (3) indicate a leptokurtic distribution, where the data has higher peaks and longer tails than when compared to normally distributed data. No variables exhibited platykurtic kurtosis (values of less than -three).

We approached data transformations conservatively (Osborne 2002; Tabachnick & Fidell, 2007). To improve normality, we transformed the measures by squaring each PERF1, PERF2, PERF3, RECOVR1, RECOVR 2, and RECOVR 3 data point. Once transformed, kurtosis and skewness values were within acceptable ranges. See Appendix C for mean, standard deviations, minimums, and maximums figures before and after the data transformation process.

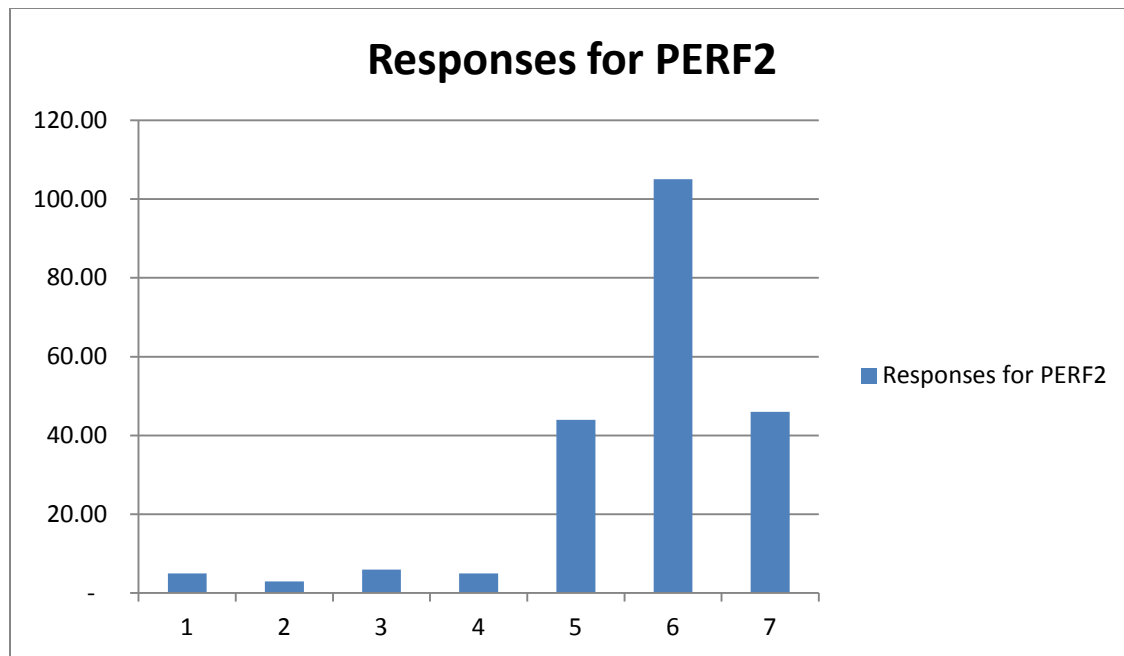


Figure 8: Distribution of responses for PERF2

### Common method bias

Common method bias (CMB) refers to variance introduced into an investigation by the method of measurement (Podsakoff, MacKenzie, & Podsakoff, 2012). Experts suggest this phenomenon can bias construct parameter estimates (Podsakoff et al., 2012) or reliability and validity estimates (Bagozzi, 1984).

Podsakoff et al. (2012) suggested addressing CMB during the instrument design phase. By changing the anchors within the instrument, investigators are able to lessen the influence of the measurement method procedurally. This helps eliminate common scale properties (Podsakoff et al., 2012). Besides changing the anchors within our survey, we used multiple rounds of Q-sorting and several preliminary tests (pilot and pre-test) to eliminate wording ambiguity.

Further, as suggested by Podsakoff et al. (2012) and Lindell and Whitney (2001), we statistically evaluated the survey with a latent factor where a directly measured item served as an indicator. Here the bias is controlled for with the communality of the latent factor (Meade, Watson, and Kroustalis, 2007). In addition, we also used an unmeasured latent method factor to control for method bias. For this, we added GREEN, a question about environmentally friendly purchasing habits, to the final survey instrument. The findings suggested that CMB is not present in our dataset. See Appendix D for details.

### **Non-response bias**

Lambert and Harrington (1990) indicated that non-response bias identifies differences between respondents and non-respondents. To assess the non-response bias, we compared early and late respondents. Specifically, we looked at responses we received by mail, as it was possible to determine when surveys were initially sent and when respondents returned the completed survey. The evidence indicates that non-response bias is not present in this study. See Appendix E for details.

### **Validation of survey instrument**

To establish reliability of the survey instruments, we estimated the internal consistency using Cronbach's alpha (Cronbach, 1951). The reliability coefficients of 0.70 or higher are typically meaningful cutoffs (Cronbach, 1951; Nunnally, 1978). Table 5 shows that the Cronbach's alpha values for the various constructs exceeded the suggested

cut-off value and ranged from 0.737 to 0.927. These results suggest that the constructs exhibit good psychometric properties. We report Cronbach's alpha as it allows us to estimate the variance associated with a set of results. It tells us that a construct or a set of questions is consistently measuring the topic of interest.

Construct	Std Loadings	Cronbach's Alpha	Composite Reliability	AVE
Internal Integration	0.914	0.812	0.826	0.67
	0.756			
	0.666			
Training	0.829	0.888	0.891	0.761
	0.839			
	0.899			
Information Sharing	0.722	0.776	0.784	0.621
	0.69			
	0.804			
Warning Capabilities	0.844	0.860	0.881	0.747
	0.938			
	0.747			
Recovery Capabilities	0.908	0.927	0.930	0.83
	0.922			
	0.872			
Performance	0.641	0.737	0.740	0.577
	0.653			
	0.776			

Table 5: Standardized path loadings from CFA and descriptive statistics

### Content validity

Content validity describes how well a measurement instrument, such as a survey, measures the proposed construct domain (Churchill, 1979). When content validity is high, the instrument is capturing the essence of the construct appropriately. Before we collected any data, we established the content validity of our survey by linking the



concepts to existing SC and RM literature. We also asked academic and practitioner experts to validate the measures during pre-test and pilot stages. Following Dillman (1978) and Dillman, Smyth, and Christian (2008), we amended questions and the measurement instrument based on the feedback about the questionnaire's readability, structure, and completeness.

### **Unidimensionality and construct reliability**

We used confirmatory factor analysis (CFA) to assess the scale's unidimensionality and construct reliability. Table 5 reports the *Cronbach's Alpha*, composite reliabilities, and the average variance extracted (AVE) for each factor. To determine the reliability of each measurement instrument, we evaluated the composite reliability. All scales had acceptable composite reliability estimates greater than 0.70 (See Table 5) (Fornell & Larcker, 1981). We also calculated the AVE for each construct to determine the amount of true score variance captured by the latent variables. Accordingly, each item set should ideally have an AVE greater than 0.50. We do not report the  $X^2$  or fit indices as each was set to the respective maximum or minimum, indicating a perfect fit. When using CFA perfect, researchers can get perfect fit scores when their model is "just identified" as it has zero degrees of freedom.

### **Criterion and concurrent validity**

Criterion-related validity indicates how well measurement scales represent the proposed constructs. To establish criterion-related validity of the constructs, we examined

the correlation of the scales with warning and recovery measures. We employed Pearson's correlation test to determine the relationships between the antecedent constructs and the outcome variables. Table 6 illustrates the correlations among various relationships. Each is statistically significant at  $p < 0.05$ . Based on the results of the correlation analysis, we concluded that the antecedent constructs have an acceptable criterion-related validity.

In addition, when constructs are highly correlated and directionally appropriate, they are said to have concurrent validity. When reviewing Table 6, we notice that all the construct appear to be directionally appropriate, as they are all positive and statistically significant at  $p < 0.05$ . Thus, we conclude that our data is concurrently valid.

Items	#of items	Internal Integration	TRAIN	INFOSHR	WARN	RECOVR	PERF
Internal Integration	3	0.82	28.67	29.29	34.57	78.39	26.47
TRAIN	3	0.48	0.87	38.93	35.18	55.02	20.67
INFOSHR	3	0.53	0.67	0.79	38.55	33.35	14.32
WARN	3	0.51	0.49	0.44	0.86	16.03	45.43
RECOVR	3	0.42	0.48	0.42	0.74	0.91	43.37
PERF	3	0.60	0.55	0.51	0.45	0.54	0.91

Table 6: Correlations<sup>1</sup> square root of average variance extracted (AVE)<sup>2</sup> and chi-square differences<sup>3</sup>

1. Correlations bottom left triangle
2. Square root of average variance extracted (AVE) on diagonal. This converts the AVE to the standard deviation scale, so it can be compared to correlations located in bottom left triangle.
3. Satorra-Bentler differences top right triangle (SBDIFF.exe)

### Discriminant validity

As the data in our study were not normally distributed, we calculated a Satorra-Bentler (S-B) difference for each pair of constructs (Satorra & Bentler, 2001). This resulted in 30 models (15 constrained and 15 unconstrained) that we used to evaluate the measurement scale's discriminate validity. Using Bryant and Satorra's (2012) scaled difference procedure, we compared a constrained model (correlations between factor pairs constrained to one (1)) to the unconstrained model (correlations between factor pairs are allowed to correlate freely).

When running a CFA on the various pairs, we expected a S-B  $X^2$  difference of at least 10.83 ( $P < 0.001$ ) in order to establish discriminant validity between constructs. The results indicate that each construct represents a unique construct and therefore has

discriminant validity (See Appendix F for input and output variables for each construct pair).

## **Analysis and Findings**

### **Respondent profile**

According to the AHA, there are 5,724 hospitals within the United States. Table 7 shows the respondent profiles, including percentage by type of care and hospital type. When considering type of hospital (bottom right portion of Table 7), 59% of respondents were from *Nongovernment Not-for-Profit Community Hospitals*. This differs significantly from the total population of hospitals. Therefore, we interpret the results cautiously.

Licensed Beds			Type of Care <sub>1</sub>				
<100 Beds	68	33%	Primary health care (i.e. broad range of ambulant and inpatient treatments)	122	82%		
101-200 Beds	44	21%	Secondary care (i.e. partially specialized) interdisciplinary and mainly inpatient treatments)	12	8%		
201-300 Beds	25	12%	Tertiary care (i.e. special clinics, incl. non-somatic care)	10	7%		
301-400 Beds	18	9%	Non-acute care (i.e. rehabilitation chronic care)	5	3%		
401-500 Beds	16	8%	Total	149	100%		
501-600 Beds	7	3%	1. First 62 respondents were not asked about type				
>601 Beds	28	14%					
Total	206	100%	Type of Hospital <sub>1</sub>				
				Sample	Total Population <sub>2</sub>		
			Non-government Not-for-Profit Community Hospital (religious affiliated)	18	12%	2,903	51%
College or University Affiliation			Non-government Not-for-Profit Community Hospital (secular not religious affiliated)	87	59%	1,025	18%
Yes	52	25%	Investor-Owned (For-Profit) Community Hospital	12	8%	1,045	18%
No	154	75%	State/Local Government Community Hospital	23	16%	208	4%
Total	206	100%	Federal Government Hospital	0	0%	421	7%
Teaching Hospital			Non-federal Long Term Care Hospital	2	1%	112	2%
			Other (Prison Hospitals, College Infirmarys, Etc.)	5	3%	10	0%
Yes	79	39%	Total	147	100%	5,724	100%
No	125	61%	1. First 62 respondents were not asked about type of hospital.				
Total	204	100%	2. Hospital fast facts retrieved from AHA.ORG 3/31/2013.				

Table 7: Respondent Profile

Initially, we evaluated the overall fit of the structural model (i.e., path and measurement model combined). Using EQS version 6.2 for Windows, we found that the model fits the data well. Table 8 presents the estimated loading and fit indices: Satorra-Bentler  $X^2 = 308.52$ ,  $df = 186$ , CFI = 0.926, and NNFI = 0.908. Furthermore, the RMSEA was 0.056 with a 90% confidence interval ranging from 0.044 to 0.067. When compared to standards established within OM literature, these relative and absolute statistics indicate acceptable fit (Hu & Bentler, 1999; Marsh, Balla, & McDonald, 1988).

Path	Unstandardized b (Standard Error)	Standardized $\beta$	Hypothesis tested
Internal integration --> WARN	0.338 (0.142)	0.347	H1A - Supported
Internal integration --> RECOVER	-0.227 (0.765)	-0.026	H1B - Not supported
Internal integration --> WARN--> RECOVER (Mediated)	2.05 (0.915)	0.235	H1C - Supported
INFOSHR --> WARN	0.050 (0.178)	0.043	H2A - Not supported
INFOSHR --> RECOVER	0.549 (1.065)	0.052	H2B - Not supported
INFOSHR --> WARN --> RECOVER (Mediated)	0.303 (1.08)	0.029	H2C - Not supported
TRAIN --> WARN	0.314 (0.128)	0.335	H3A - Supported
TRAIN --> RECOVER	0.815 (1.193)	0.086	H3B - Not supported
TRAIN --> WARN --> RECOVER (Mediated)	1.905 (0.827)	0.227	H3C - Supported
TRAINxBEDS --> WARN	0.058 (0.045)	0.12	H4A - Not supported
TRAINxBEDS --> RECOVER	-0.441 (0.216)	-0.105	H4B - Supported
TRAINxBEDS --> WARN --> RECOVER (Mediated)	0.351 (0.278)	0.081	H4C - Not supported
WARN --> RECOVER	6.067 (0.913)	0.677	H5 - Supported
WARN --> PERF	1.398 (1.039)	0.173	H6A - Not supported
WARN --> RECOVER --> PERF (Mediated)	2.317 (0.790)	0.287	H6B - Supported
RECOVER --> PERF	0.382 (0.117)	0.424	H6C - Supported
<b>Control Variable</b>			
BEDS --> WARN	0.001 (0.035)	0.002	Not Supported
BEDS --> RECOVER	0.682 (0.218)	0.136	Supported
BEDS --> PERF	0.107 (0.321)	0.024	Not Supported
<b>Absolute and Incremental Fit</b>		<b>Value</b>	
SATORRA-BENTLER- $X^2$		308.52	
Degrees of Freedom		186	
COMPARATIVE FIT INDEX (CFI)		0.917	
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)		0.056	
90% CONFIDENCE INTERVAL OF RMSEA		(0.044 - 0.067)	

Table 8: Coefficients and robust fit statistics.

### **Internal integration (H1A-C)**

The relationship between internal integration and WARN (H1A) was positive and significant ( $\beta = 0.347$ ,  $p = 0.0184$ ). This suggests that organizations can improve their scanning and communication abilities by developing internal systems and processes to connect with other employees and departments. Braunscheidel and Suresh (2009) found similar results when linking internal integration with SC agility. In their study, they investigated the antecedent competencies that enable SC agility in the mitigation context. From an HRT perspective, internal integration is similar to the concept of coupling. Tight coupling enables practitioners to exercise control over operational processes (Roe & Schulman, 2008). Without control, practitioners would find it difficult to develop highly reliable organizations.

The path coefficient from internal integration to RECOVR (H1B) was not significant ( $\beta = -0.026$ ,  $p = 0.7676$ ). This finding surprises us since other risk mitigation research has shown how internal integration can enhance connectivity and coordination (Braunscheidel & Suresh, 2009). While similar, the Braunscheidel and Suresh research linked internal integration to SC agility, which practitioners used to mitigate and respond to SC disruptions. We believe our results indicate that when responding to a SC disruption that responders may need to decouple themselves from existing procedures and adapt to the surrounding environment. HRT proponents call the decoupling process latitude for improvisation (Weick, 1987). Improvisation may not be necessary with every

type of SC disruption; however, when needed, it allows a practitioner to create unique response tactics.

We also found that internal integration has a mediated relationship with RECOVER via the WARN construct (H1C). The relationship from WARN to RECOVER was significant ( $\beta = 0.677$ ,  $p < 0.0001$ ). Therefore, the resultant indirect effect equals  $\beta=0.235$ . To confirm the fully mediated effect between internal integration and RECOVER, we followed Selig and Preacher's (2008) recommendation and conducted a bootstrap analysis to determine whether the relationship is significant. Using 20,000 bootstrap estimates, we identified a significant relationship. The 95% confidence interval (CI) ranged from 0.3321 to 3.985 (see Appendix G for distribution of indirect effects).

As the bootstrapping process did not capture zero within the 95% confidence interval, we acknowledged that the fully mediated relationship (as opposed to a partially mediated) is significant. Thus, internal integration is positively associated with WARN which in turn is positively associated with RECOVER.

### **Information sharing (H2A-C)**

Both pathways INFOSHR to WARN (H2A) ( $\beta = 0.043$ ,  $P= 0.7767$ ) and INFOSHR to RECOVER (H2B) ( $\beta = 0.052$ ,  $p= 0.6072$ ) were not significant. These findings are surprising, since existing research repeatedly demonstrated that INFOSHR significantly affects an organization's RM and risk mitigation efforts (Chopra & Sodhi, 2004; Faisal, Banwet, & Shankar, 2006; Speckman & Davis, 2004). We suspect the relationships are non-significant due to the context of the investigation. Perhaps hospital



material managers do not rely on INFOSHR abilities as much as managers in other industries do. Researchers have previously found that “information sharing is especially difficult among companies that are remotely located in the supply chain” (Ahn & Lee, 2004, p. 18). During initial interviews, one hospital procurement director indicated that it was common to locate procurement functions at offsite locations.

As both direct relationships were insignificant, we presumed that the indirect relationship from INFOSHR through WARN to RECOVER would also be insignificant. Using the bootstrap methodology, we confirmed that the 95% confidence interval includes zero values (See Appendix H for the distribution of indirect effects). This suggests that the indirect effects are non-significant,  $\beta=0.029$ .

### **Training (H3A-C)**

The coefficient between TRAIN and WARN (H3A) was positive and significant ( $\beta = 0.335$   $p= 0.0157$ ). This evidence implies that managers can train practitioners to scan for and communicate information about SC disruptions. Sheffi, Rice, Fleck, & Caniato (2003) confirmed that TRAIN activities, such as simulation and gaming, help organizations build resilience. When viewed through the HRT lens, training enhances reliability, which is used to combat SC disruption (Tamuz & Harrison, 2006).

When evaluating the relationship between TRAIN and RECOVER (H3B), we found that their direct association was not significant ( $\beta = 0.086$   $p= 0.4955$ ). Following HRT logic, we expected TRAIN activities to support and enhance pre-emptive and

reactive response tactics. However, the insignificant findings suggest that training alone will not improve or worsen an organization's response capabilities. We believe that because SC disruptions vary widely in makeup and consequences, therefore, practitioners need more diverse types of training activities if managers expect TRAIN to affect RECOVER.

For hypothesis 3C, we anticipated the WARN construct to mediate the link between TRAIN and RECOVER. Our results indicated that a construct within a chain of events could be important yet have a minimal direct effect on specific construct (Vickery, Jayaram, Droge, & Calantone, 2003). Specifically, we found the indirect relationship to be significant ( $\beta = 0.086$ ) and fully mediated. We used the bootstrapping methodology to confirm the significance. See Appendix I for distribution of indirect effects. The 95% confidence interval (CI) ranged from 0.4046 to 4.146. Since the CI did not include zero, the results indicated that TRAIN-RECOVER relationship is significant and fully mediated by the WARN construct.

#### **The moderating effect of organization size on training (H4A-C)**

Following the recommendation of Marsh, Wen and Hau (2004), we mean-centered both independent and moderating variables prior to creating the interaction variable. This allows us to avoid multi-collinearity between constructs (Venkatraman, 1989). We then tested the relationship between TRAINxBEDS and WARN (H4A). We originally hypothesized that training would augment the WARN construct positively

when moderated by organization size (BEDS). Our analysis indicated that the hospital size does not significantly moderate the TRAIN-WARN relationship ( $\beta = 0.012$ ,  $p = 0.2053$ ).

In hypothesis 3A, we found that TRAIN significantly and positively affects the WARN construct. When combined with the insignificant results from H4A, we concluded that BEDS, a proxy for organization size, does not interact and alter the relationship. Thus, this seems to imply that WARN related training is important regardless of organization size.

The path coefficient from TRAINxBEDS to RECOVR (H4B) was significant ( $\beta = -0.105$ ,  $p = 0.0425$ ). This indicates that the TRAIN-RECOVR relationship does lessen as organization size increases. To interpret this result, we report simple slopes, as prescribed by Aiken and West (1992). (See Figure 9)

- *Simple slope for TRAIN at +1 standard deviations of BEDS*  $= 0.815 + (-0.441 * 1 * 2.10) = -0.1111$
- *Simple slope for disruption sensing and response capability at mean of recovery capability*  $= 0.815$
- *Simple slope for TRAIN at -1 standard deviations of BEDS*  $= 0.815 + (-0.441 * -1 * 2.10) = 1.7411$

This evidence suggests that a one-unit increase in TRAIN increases the RECOVR by -0.1111 units as the number of BEDS increases (larger organizations). At the average number of BEDS, a one-unit increase of TRAIN abilities marginally improves the response capabilities by 0.815. Lastly, when a hospital has a small number of BEDS

(small organizations), a one-unit increase in TRAIN improves the organization's RECOVER by 1.7411.

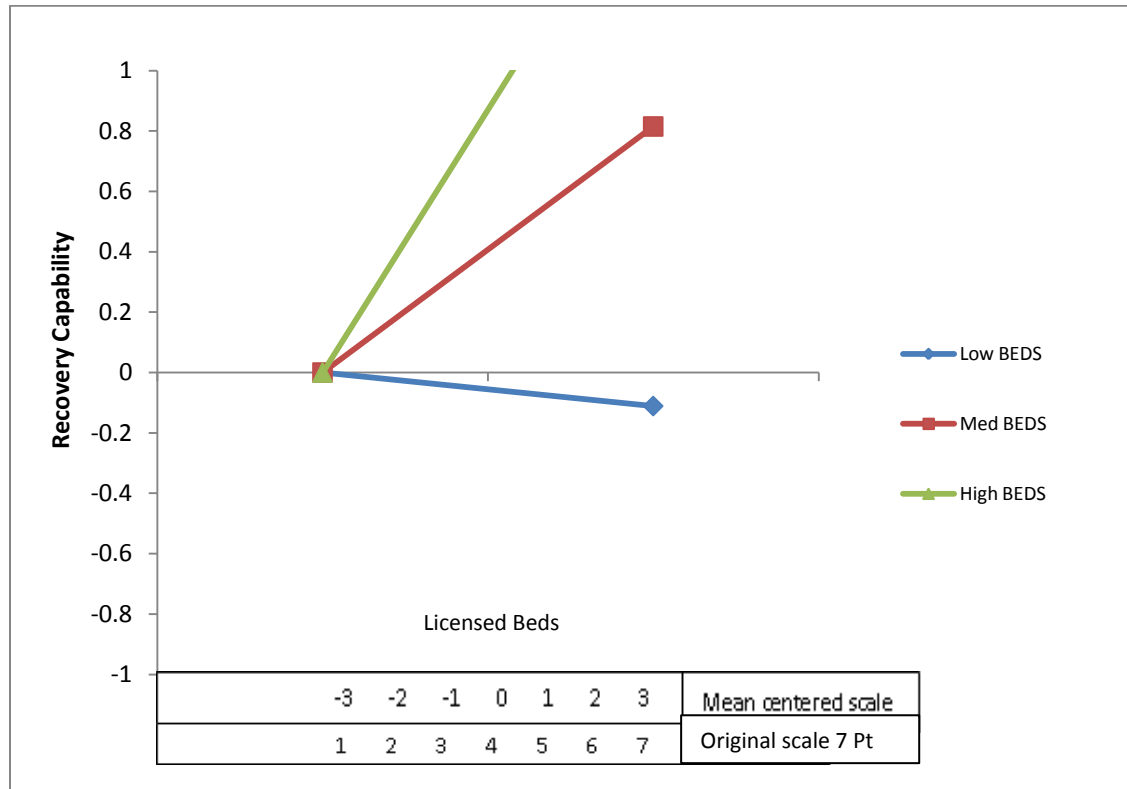


Figure 9: Simple Slopes for TRAIN x BEDS interaction

Lastly, in H4C we proposed that the moderating effect of TRAINxBEDS on RECOVER was mediated by WARN. In testing the mediated moderation effect (TRAIN\*BEDS) >> WARN >> RECOVER), the point estimate (0.351) is the product of the estimates for the effect of WARN on the TRAIN\*BEDS interaction term (0.058) and the effect of RECOVER on WARN (6.067) (Tein, Sandler, MacKinnon, & Wolchik, 2004). The standard error of this effect is  $5.539 = [(0.058^2)(0.045^2) + (6.067^2)(0.913^2)]^{1/2}$ .

Thus we conclude that the mediated moderation effect was not significant [0.351 (5.539),  $Z=0.07$ ].

However, to illustrate the moderating effects of BEDS, we also calculate the conditional mediation effects using the simple slopes from the three “a” coefficients and then multiplying by the single “b” coefficient (WARN >> RECOVER) (Preacher, Rucker, & Hayes, 2007). The results indicate that TRAIN may indirectly improve RECOVER within small and medium hospitals. In particular, training activities have a positive indirect effect (10.56), in hospitals with a small number of BEDS. Likewise, in medium size hospitals, we find a positive indirect effect, however the overall effect is reduced (4.94). The impact of TRAIN continues to diminish as hospital size increases. Thus, in large hospitals we found that TRAIN has a slight negative indirect effect (-0.674). Overall, these results suggest that as hospital size increases, the mediated influence of TRAIN on RECOVER decreased.

### **Warning capabilities to recovery capabilities (H5)**

When Craighead et al. (2007) defined warning and recovery capabilities; they postulated that the constructs were related. Following this thinking, we proposed a positive relationship from WARN to RECOVER (H5A). After analyzing the pathway, we found a positive and significant ( $\beta = 0.677$ ,  $p < 0.0001$ ) relationship. This supports

previous research asserting that warning capabilities, such as prevention and detection, are antecedents to response and recovery efforts (Price, 2004).

### **The effect of warning and recovery capabilities on organizational performance**

#### **(H6A-C)**

When analyzing the relationship between WARN to PERF (H6A), we found a non-significant effect ( $\beta = 0.173$ ,  $p=0.1799$ ). This finding surprised us, as WARN was hypothesized to improve both scanning and communication capabilities. With this non-supportive evidence, we assume that while useful the WARN are costly to the organization. Stated differently, managers must expend financial and physical resources to enable WARN tactics. We suspect that some organizations, perhaps entrepreneurial firms, are able to make use of these competencies. For example, Shepherd et al. (2007) found that environmental scanning activities helped generate entrepreneurial ideas. Within an entrepreneurial firm, we would expect scanning abilities to enhance performance.

When considering the WARN – PERF relationship, we must account for the RECOVR construct as an intermediary (H6B). The evidence suggests that RECOVR mediates the relationship and creates an indirect effect ( $\beta = 0.287$ ). We confirmed the relationship using bootstrapping. See Appendix J for the distribution of indirect effects. This augmented relationship demonstrates that organizations should develop WARN as a means to enhance performance. However, managers will need to develop both warning and recovery capabilities to see improvement.

The relationship between RECOVR and PERF (H6C) is significant ( $\beta = 0.424$ ,  $p=0.0013$ ). This confirms our thinking that organizations can develop proactive and reactive response capabilities as a means to improve performance. When designing recovery capabilities, managers should develop processes that jumpstart response efforts. Documented processes and a clear chain of command enable first responders to initiate recovery with a clear line of authority (Gebbie & Qureshi, 2002). Yet both the processes and the supporting hierarchy need to allow practitioners to adapt when necessary. Responders should apply problem-solving skills and adapt to the disruption within the confines of their position (Gebbie & Qureshi, 2002).

### **Control variables**

We test four control variables within this research: university affiliated (UNIV), teaching hospital (TEACH), type of care (TYPE), and organization class (CLASS). While, neither UNIV nor TEACH had any significant effects, both TYPE and CLASS warranted further investigation (See Table 8). When evaluating both TYPE and CLASS we found the influence was not meaningful, as it did not change the significance of any relationships initially identified in the base model.

Control Variables	Yes or No	Yes or No	4 Choices	8 Choices
Absolute and Incremental Fit	UNIV	TEACH	TYPE	CLASS
WARN	0.160 (0.158)	0.115 (0.146)	0.234 (0.093)***	0.005 (0.101)
RECOVR	-1.568 (1.202)	1.031 (1.069)	-1.658 (0.567)***	-0.652 (0.351)
PERF	0.053 (1.257)	0.724 (1.142)	0.777 (0.777)	-1.317 (0.484)**
SATORRA-BENTLER- $\chi^2$	376.6	374.4306	339.8301	331.9441
Degrees of Freedom	205	205	205	205
COMPARATIVE FIT INDEX (CFI)	0.89	0.892	0.913	0.915
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)	0.063	0.063	0.056	0.054
90% CONFIDENCE INTERVAL OF RMSEA	(0.053 - 0.073)	(0.052 - 0.072)	(0.045 - 0.066)	(0.043 - 0.064)
Notes: *** Significant to 0.0001; ** Significant to 0.001;				

Table 9: Control variables with Fit, unstandardized betas and standard errors

## **Conclusions**

This research contributes to the SC and RM literature in several ways. First, the results suggest that by developing a reliable SC, managers can enhance the organization's RM capabilities and performance. To achieve improved performance, managers should design reliability-oriented systems that are decentralized in nature and run by mindful practitioners who understand and care for the organization.

Second, we developed new measures to assess organizational warning and recovery capabilities. While originally defined by Craighead et al. in 2007, we operationalize them within the SC and RM context. Using interviews, sorting procedures, and confirmatory factor analysis, we developed valid and reliable measures that both academics and practitioners can use to benchmark and understand an organization's RM capabilities. For WARN, our evidence suggests that managers can scan for SC anomalies and then communicate information about SC threats to partners within an organization.



Our study also confirmed that RECOVR allows the organization to address SC disruption both before (pre-emptive) and after (reactive) a disruption occurs.

Third, the findings indicated that several competencies positively affect an organization's RM capabilities. For example, both internal integration and TRAIN affect WARN directly and RECOVR indirectly. Our evidence suggests that managers can develop organizational structures as a means to combat SC risk. We advocate the use of these behavior-based RM competencies because they develop the employees and the organization itself rather than just investing in resources and buffers that may never be used.

Fourth, we found that both warning and recovery capabilities affect organizational performance. Our findings indicate a direct connection between RECOVR and PERF. This suggests that managers can develop response capabilities to mitigate a SC disruption's influence and/or lessen the time it takes for the SC to return to a steady state. This is important, as organizations compete on the speed of their operation functions, especially in the face of a SC disruption. Ensuring that the organization can quickly recover from a SC disruption should help the organization retain existing customers and acquire new customers when the competition is struggling to recover.

Although we found no direct relationship between WARN and PERF, the evidence indicates an indirect effect when RECOVR serves as a mediator. This signifies that managers should develop scanning and communication competencies within an organization, as a method to enhance performance. However, to benefit from the improved abilities, the organization must develop both the warning and recovery

capabilities, as WARN depends on RECOVER. Stated differently, warning capabilities alone without recovery capabilities is not sufficient.

Fifth, the research explored organization size (BEDS) as a moderator of the relation between TRAIN and PERF. The results show that as the number of licensed beds increases, the rate at which TRAIN affects PERF diminishes. Stated differently, as a hospital grows in size, training becomes less effective at improving PERF. This implies that procurement managers of large hospitals must work harder for TRAIN to influence an organization's RM capabilities.

### **Limitation and Future Research Opportunities**

As with any investigation, our research has limitations. First, we collected data from 215 hospital procurement professionals. Choosing one industry allows us to control for variation associated with different industries (Eisenhardt, 1989). However, it limits the generalizability of the findings (Cool & Schendel, 1987; Safizadeh, Ritzman, & Mallick, 2000). Replicating this research within other industries would add to our understanding of the values of behavioral-based risk management techniques. Second, we drew inferences from cross sectional data. Longitudinal data would improve our understanding of these RM phenomena and the discussion concerning causality (Rosenzweig, Roth, & Dean, 2003). Third, we were also concerned with the utility of the warning and recovery measures. Since this is one of the first studies to operationalize these constructs, it would be beneficial to strengthen these measures with additional

testing. Lastly, we were concerned about using single respondents to answer our survey. This issue has been widely discussed in the literature (Podsakoff & Organ, 1986). To address potential problems, we structured our survey according to the best practices and tested for common method bias. Additional studies could collect data from multiple respondents and sources.

During this investigation, we obtained several interesting results that spur future research. Initially, we envisioned improvement in the WARN and RECOVER constructs. Using the new constructs in follow-up studies provides additional validity and reliability testing. Second, while our research looks at structural competencies, future studies should test other antecedents. Examples include information system integration, managerial attitudes towards improvisation, and quality management systems. Finally, we used perceptual measures for organizational performance. While these are helpful for interpretation and measurement, objective outcomes, like gross earnings, actual profit, and in-stock level would be more definitive outcome variables. During this research process, we found that some hospitals regularly publish profit and loss data. However, many private and non-profit hospitals provide very little information about financial performance.

## Appendices

### Appendix A: Correlations, means, and standard deviations for each item

Correlations	II1	II2	II3	INFOSHR1	INFOSHR2	INFOSHR3	TRAIN1	TRAIN2	TRAIN3	WARN1	WARN2	WARN3	RECOVER1	RECOVER2	RECOVER3	PERF1	PERF2	PERF3	GRN
II1	1.00																		
II2	0.69	1.00																	
II3	0.60	0.52	1.00																
INFOSHR1	0.34	0.27	0.29	1.00															
INFOSHR2	0.33	0.27	0.33	0.46	1.00														
INFOSHR3	0.39	0.28	0.27	0.58	0.58	1.00													
TRAIN1	0.39	0.31	0.33	0.44	0.45	0.48	1.00												
TRAIN2	0.40	0.35	0.35	0.49	0.42	0.44	0.66	1.00											
TRAIN3	0.39	0.28	0.30	0.50	0.36	0.42	0.76	0.76	1.00										
WARN1	0.43	0.31	0.44	0.25	0.27	0.37	0.33	0.42	0.37	1.00									
WARN2	0.41	0.37	0.38	0.23	0.27	0.39	0.39	0.44	0.38	0.80	1.00								
WARN3	0.38	0.33	0.27	0.20	0.21	0.23	0.31	0.37	0.38	0.55	0.71	1.00							
REC1	0.38	0.26	0.30	0.30	0.26	0.30	0.36	0.41	0.43	0.62	0.61	0.59	1.00						
REC2	0.39	0.30	0.33	0.30	0.21	0.31	0.32	0.42	0.39	0.64	0.63	0.55	0.86	1.00					
REC3	0.29	0.26	0.29	0.30	0.28	0.32	0.34	0.39	0.37	0.56	0.62	0.66	0.78	0.80	1.00				
PERF1	0.50	0.42	0.31	0.20	0.24	0.31	0.31	0.32	0.34	0.29	0.27	0.24	0.31	0.32	0.27	1.00			
PERF2	0.43	0.26	0.26	0.13	0.27	0.18	0.23	0.31	0.28	0.25	0.20	0.15	0.36	0.36	0.27	0.54	1.00		
PERF3	0.44	0.31	0.25	0.32	0.32	0.33	0.38	0.43	0.42	0.45	0.43	0.35	0.55	0.54	0.48	0.44	0.65	1.00	
GRN	0.19	0.20	0.28	0.21	0.25	0.28	0.37	0.32	0.29	0.23	0.17	0.16	0.13	0.18	0.20	0.24	0.05	0.16	1.00
Standard Deviation	1.35	1.31	1.61	1.21	1.39	1.25	1.45	1.35	1.37	1.16	1.27	1.51	1.14	1.12	1.28	1.34	1.22	1.20	1.34
Mean	5.17	4.91	4.50	5.68	5.59	5.72	5.05	5.42	5.19	5.54	5.58	5.35	5.88	5.96	5.78	5.01	5.71	5.83	4.53

## **Appendix B: Survey questions**

### *Internal integration*

1. Within my organization, there are mechanisms in place to encourage internal integration.
2. I believe different departments within my organization are properly integrated.
3. We have project managers who integrate activities across the organization.

### *Performance*

4. My organization is able to keep operating costs to a minimum.
5. My organization is able to keep out of stocks to a minimum.
6. My organization is able to keep service quality high.

### *Warning capabilities*

7. My organization has procedures to identify threats.
8. Within my organization, there are systems to warn employees about potential threats.
9. Within my organization, the command center identifies actual disruptions.

### *Recovery capabilities*

10. When a disruption occurs, my organization immediately starts recovery efforts.
11. Once a threat is identified, my organization deploys resources to reduce the negative effects.
12. My organization's command center deploys recovery resources to reduce the effects of a disruption.

### *Training*

13. Within my organization, employees are cross-trained so they can fill in for others if necessary.
14. Within my organization, there are employee training resources available.
15. Employees receive training to perform multiple tasks.

*Information sharing*

16. Most people within my organization believe that sharing information is important.
17. In my opinion, finance shares information with operations.
18. Managers from departments across the organization are expected to share information with others.

*Control variables*

19. How many beds does your organization have?
20. Is your organization affiliated with a college or university?
21. Is your organization a teaching facility?
22. What type of care does your organization provide?
  - a. Primary health care (i.e. broad range of ambulant and inpatient treatments)
  - b. Secondary care (i.e. partially specialized) interdisciplinary and mainly inpatient treatments)
  - c. Tertiary care (i.e. special clinics, incl. non-somatic care)
  - d. Non-acute care (i.e. rehabilitation chronic care)
23. How would you classify your organization?
  - a. Non-government Not-for-Profit Community Hospital (religious affiliated)

- b. Non-government Not-for-Profit Community Hospital (secular not religious affiliated)
- c. Investor-Owned (For-Profit) Community Hospital
- d. State/Local Government Community Hospital
- e. . Federal Government Hospital
- f. Non-federal Long Term Care Hospital
- g. Other (Prison Hospitals, College Infirmarys, Etc.)
- h. Nonfederal Psychiatric Hospital

## Appendix C: Descriptive statistics before transformation

Original Data Set: 215 responses before tranformation								
NAME	CASES	MEAN	StdDev	Min	Max	Range	Skewness	Kurtosis
Internal integration 1	215	5.17	1.35	1.00	7.00	6.00	(1.00)	1.04
Internal integration 2	215	4.91	1.31	1.00	7.00	6.00	(0.85)	0.39
Internal integration 3	215	4.51	1.60	1.00	7.00	6.00	(0.54)	(0.52)
INFORSHR 1	215	5.68	1.21	1.00	7.00	6.00	(1.30)	2.01
INFORSHR 2	215	5.59	1.39	1.00	7.00	6.00	(1.30)	1.41
INFORSHR 3	215	5.73	1.25	1.00	7.00	6.00	(1.41)	2.28
TRAIN 1	215	5.05	1.45	1.00	7.00	6.00	(0.82)	0.24
TRAIN 2	215	5.42	1.35	1.00	7.00	6.00	(1.03)	0.78
TRAIN 3	215	5.19	1.37	1.00	7.00	6.00	(0.99)	0.66
WARN1	215	5.54	1.16	1.00	7.00	6.00	(1.36)	2.85
WARN2	215	5.58	1.27	1.00	7.00	6.00	(1.51)	2.74
WARN3	215	5.35	1.51	1.00	7.00	6.00	(1.19)	1.05
RECOVR1	215	5.88	1.14	1.00	7.00	6.00	(1.55)	3.82
RECOVR2	215	5.96	1.12	1.00	7.00	6.00	(1.86)	5.50
RECOVR3	215	5.78	1.28	1.00	7.00	6.00	(1.53)	2.74
PERF1	215	5.01	1.33	1.00	7.00	6.00	(1.09)	1.05
PERF2	215	5.78	1.23	1.00	7.00	6.00	(1.82)	4.07
PERF3	215	5.83	1.20	1.00	7.00	6.00	(1.97)	5.11
BED	215	3.05	2.10	1.00	7.00	6.00	0.78	(0.74)
UNIV	215	1.74	0.43	1.00	2.00	1.00	(1.12)	(0.72)
TEACH	215	1.60	0.48	1.00	2.00	1.00	(0.42)	(1.79)
TYPE	215	1.33	0.64	1.00	4.00	3.00	2.56	6.69
CLASS	215	2.50	1.13	1.00	8.00	7.00	2.27	7.31



### Appendix C (continued): Descriptive statistics after transformation

Transformed Data Set: 215 responses after transformation								
NAME	CASES	MEAN	StdDev	Min	Max	Range	Skewness	Kurtosis
IIMC1	215	-	1.35	(4.16)	1.83	6.00	(1.00)	1.04
IIMC2	215	-	1.31	(3.91)	2.08	6.00	(0.85)	0.39
IIMC3	215	-	1.60	(3.51)	2.49	6.00	(0.54)	(0.52)
ISMC1	215	-	1.21	(4.67)	1.32	6.00	(1.30)	2.01
ISMC2	215	-	1.39	(4.58)	1.41	6.00	(1.30)	1.41
ISMC3	215	-	1.25	(4.72)	1.27	6.00	(1.41)	2.28
TRNMC1	215	-	1.45	(4.04)	1.95	6.00	(0.82)	0.24
TRNMC2	215	-	1.35	(4.41)	1.58	6.00	(1.03)	0.78
TRNMC3	215	-	1.37	(4.19)	1.81	6.00	(0.99)	0.66
BEDMC	215	-	2.10	(2.04)	3.95	6.00	0.78	(0.74)
BEDXTRN1	215	0.08	2.88	(12.05)	8.28	20.34	(0.32)	2.32
BEDXTRN2	215	0.42	2.81	(13.51)	9.04	22.56	(0.52)	5.14
BEDXTRN3	215	0.25	2.74	(12.61)	8.57	21.19	(0.27)	3.35
WC1SQRD	215	31.98	11.25	1.00	49.00	48.00	(0.42)	0.06
WC2SQRD	215	32.79	12.04	1.00	49.00	48.00	(0.63)	0.06
WC3SQRD	215	30.93	13.77	1.00	49.00	48.00	(0.44)	(0.59)
RC1SQRD	215	35.90	11.61	1.00	49.00	48.00	(0.61)	(0.02)
RC2SQRD	215	36.74	11.27	1.00	49.00	48.00	(0.74)	0.40
RC3SQRD	215	35.02	12.53	1.00	49.00	48.00	(0.72)	(0.05)
PER1SQRD	215	26.89	11.66	1.00	49.00	48.00	(0.28)	(0.18)
PER2SQRD	215	34.92	11.75	1.00	49.00	48.00	(0.85)	0.68
PER3SQRD	215	35.45	11.46	1.00	49.00	48.00	(0.88)	0.86

## Appendix D: Common method bias: Method factor and marker variable

Factor		Item	Without Factor		With Method Factor Added		With Marker variable (GRN) added	
			Trait Loading	Trait Loading	Sqd Factor Loadings		Trait Loading	Sqd Factor Loadings
Internal Integration	InternalIntegration1		0.918	0.903	0.07		0.899	0.01
	InternalIntegration2		0.739	0.68	0.06		0.789	0.01
	InternalIntegration3		0.672	0.59	0.09		0.635	0.02
Training	TRAIN1		0.718	0.636	0.14		0.769	0.05
	TRAIN2		0.721	0.673	0.09		0.812	0.04
	TRAIN3		0.805	0.719	0.11		0.867	0.03
Information Sharing	INFOSHR1		0.86	0.786	0.09		0.698	0.01
	INFOSHR2		0.833	0.759	0.09		0.699	0.02
	INFOSHR3		0.916	0.98	0.01		0.783	0.03
Performance	PERF1		0.846	0.772	0.12		0.54	0.02
	PERF2		0.929	0.878	0.13		0.621	0.00
	PERF3		0.757	0.686	0.13		0.814	0.01
Warning Capabilities	WARN1		0.91	0.887	0.06		0.868	0.01
	WARN2		0.922	0.874	0.08		0.942	0.01
	WARN3		0.871	0.8	0.12		0.743	0.01
Recovery Capabilities	RECOVER1		0.667	0.66	0.02		0.904	0.00
	RECOVER2		0.713	0.751	0.00		0.916	0.01
	RECOVER3		0.779	0.714	0.09		0.862	0.01
S-B Chi2			219.37	165.41		221.58		
CFI			0.913	0.944		0.921		
RMSEA			0.063	0.054		0.062		

## Appendix E: Non-response bias results

Group Statistics										
Group		N	Mean	Std. Deviation	Std. Error Mean					
BED	1.00	15	2.133333	1.3020131	.3361783					
	2.00	15	3.000000	1.6903085	.4364358					
UNIV	1.00	15	1.866667	.3518658	.0908514					
	2.00	15	1.800000	.4140393	.1069045					
TEACH	1.00	15	1.677327	.4738894	.1223577					
	2.00	15	1.800000	.4140393	.1069045					
Independent Samples Test										
Equality of Variances						t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Interval of the	
BED	Equal variances assumed	.070	.793	-1.573	28	.127	-.8666667	.5509011	-1.9951365	.2618032
	Equal variances not assumed			-1.573	26.288	.128	-.8666667	.5509011	-1.9984576	.2651242
UNIV	Equal variances assumed	.924	.345	.475	28	.638	.0666667	.1402945	-.2207135	.3540469
	Equal variances not assumed			.475	27.290	.638	.0666667	.1402945	-.2210507	.3543841
TEACH	Equal variances assumed	2.072	.161	-.755	28	.457	-.1226733	.1624807	-.4555000	.2101533
	Equal variances not assumed			-.755	27.505	.457	-.1226733	.1624807	-.4557703	.2104236

## **Appendix F: Satorra-Bentler difference results**

### *Internal integration & TRAIN*

#### INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 117.42

Normal chi square for the MORE constrained model= 187.02

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 7.67

Normal chi square for the LESS constrained model= 7.75

Degrees of freedom for the LESS constrained model= 8

#### OUTPUTS:

Satorra-Bentler Scaled Difference = 28.6774 df = 1

Chi Square probability = 0.000000

### *Internal integration & INFOSHR*

#### INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 84.21

Normal chi square for the MORE constrained model= 128.03

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 7.87

Normal chi square for the LESS constrained model= 9.48

Degrees of freedom for the LESS constrained model= 8

#### OUTPUTS:

Satorra-Bentler Scaled Difference = 29.2955 df = 1

Chi Square probability = 0.000000

*Internal integration & WARN*

INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 115.78

Normal chi square for the MORE constrained model= 185.77

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 17.96

Normal chi square for the LESS constrained model= 21.77

Degrees of freedom for the LESS constrained model= 8

OUTPUTS:

Satorra-Bentler Scaled Difference = 34.5738 df = 1

Chi Square probability = 0.000000

*Internal integration & RECOVR*

INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 160.98

Normal chi square for the MORE constrained model= 198.59

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 5.46

Normal chi square for the LESS constrained model= 5.9

Degrees of freedom for the LESS constrained model= 8

OUTPUTS:

Satorra-Bentler Scaled Difference = 78.3932 df = 1

Chi Square probability = 0.000000

#### *Internal integration & PERF*

INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 79.11

Normal chi square for the MORE constrained model= 102.45

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 14.84

Normal chi square for the LESS constrained model= 15.53

Degrees of freedom for the LESS constrained model= 8

OUTPUTS:

Satorra-Bentler Scaled Difference = 26.4732 df = 1

Chi Square probability = 0.000000

#### *TRAIN & INFOSHR*

INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 69.20

Normal chi square for the MORE constrained model= 125.09

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 23.74

Normal chi square for the LESS constrained model= 41.94

Degrees of freedom for the LESS constrained model= 8

OUTPUTS:

Satorra-Bentler Scaled Difference = 38.9311 df = 1

Chi Square probability = 0.00000

*TRAIN & WARN*

INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 144.00

Normal chi square for the MORE constrained model= 304.73

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 20.56

Normal chi square for the LESS constrained model= 28.79

Degrees of freedom for the LESS constrained model= 8

OUTPUTS:

Satorra-Bentler Scaled Difference = 35.1817 df = 1

Chi Square probability = 0.000000

*TRAIN & RECOVR*

INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 234.06

Normal chi square for the MORE constrained model= 423.15

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 15.56

Normal chi square for the LESS constrained model= 17.30

Degrees of freedom for the LESS constrained model= 8

#### OUTPUTS:

Satorra-Bentler Scaled Difference = 55.0214 df = 1

Chi Square probability = 0.000000

#### *TRAIN & PERF*

#### INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 86.37

Normal chi square for the MORE constrained model= 125.00

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 21.22

Normal chi square for the LESS constrained model= 21.24

Degrees of freedom for the LESS constrained model= 8

#### OUTPUTS:

Satorra-Bentler Scaled Difference = 20.6783 df = 1

Chi Square probability = 0.000005

#### *INFOSHR & WARN*



INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 111.00

Normal chi square for the MORE constrained model= 165.53

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 7.19

Normal chi square for the LESS constrained model= 8.40

Degrees of freedom for the LESS constrained model= 8

OUTPUTS:

Satorra-Bentler Scaled Difference = 38.5592 df = 1

Chi Square probability = 0.000000

*INFOSHR & RECOVR*

INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 106.76

Normal chi square for the MORE constrained model= 163.38

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 8.39

Normal chi square for the LESS constrained model= 9.61

Degrees of freedom for the LESS constrained model= 8

OUTPUTS:

Satorra-Bentler Scaled Difference = 33.3569 df = 1

Chi Square probability = 0.000000

*INFOSHR & PERF*

INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 68.09

Normal chi square for the MORE constrained model= 125.59

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 21.11

Normal chi square for the LESS constrained model= 25.34

Degrees of freedom for the LESS constrained model= 8

OUTPUTS:

Satorra-Bentler Scaled Difference = 14.3272 df = 1

Chi Square probability = 0.000154

*WARN & RECOVR*

INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 83.16

Normal chi square for the MORE constrained model= 182.93

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 36.15

Normal chi square for the LESS constrained model= 52.78

Degrees of freedom for the LESS constrained model= 8

OUTPUTS:

Satorra-Bentler Scaled Difference = 16.0335 df = 1

Chi Square probability = 0.000062

#### *WARN & PERF*

##### INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 121.85

Normal chi square for the MORE constrained model= 156.60

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 30.87

Normal chi square for the LESS constrained model= 34.24

Degrees of freedom for the LESS constrained model= 8

##### OUTPUTS:

Satorra-Bentler Scaled Difference = 45.4306 df = 1

Chi Square probability = 0.000000

#### *RECOVR & PERF*

##### INPUTS:

Satorra-Bentler chi square for the MORE constrained model= 101.09

Normal chi square for the MORE constrained model= 129.92

Degrees of freedom for the MORE constrained model= 9

Satorra-Bentler chi square for the LESS constrained model= 22.64

Normal chi square for the LESS constrained model= 25.95

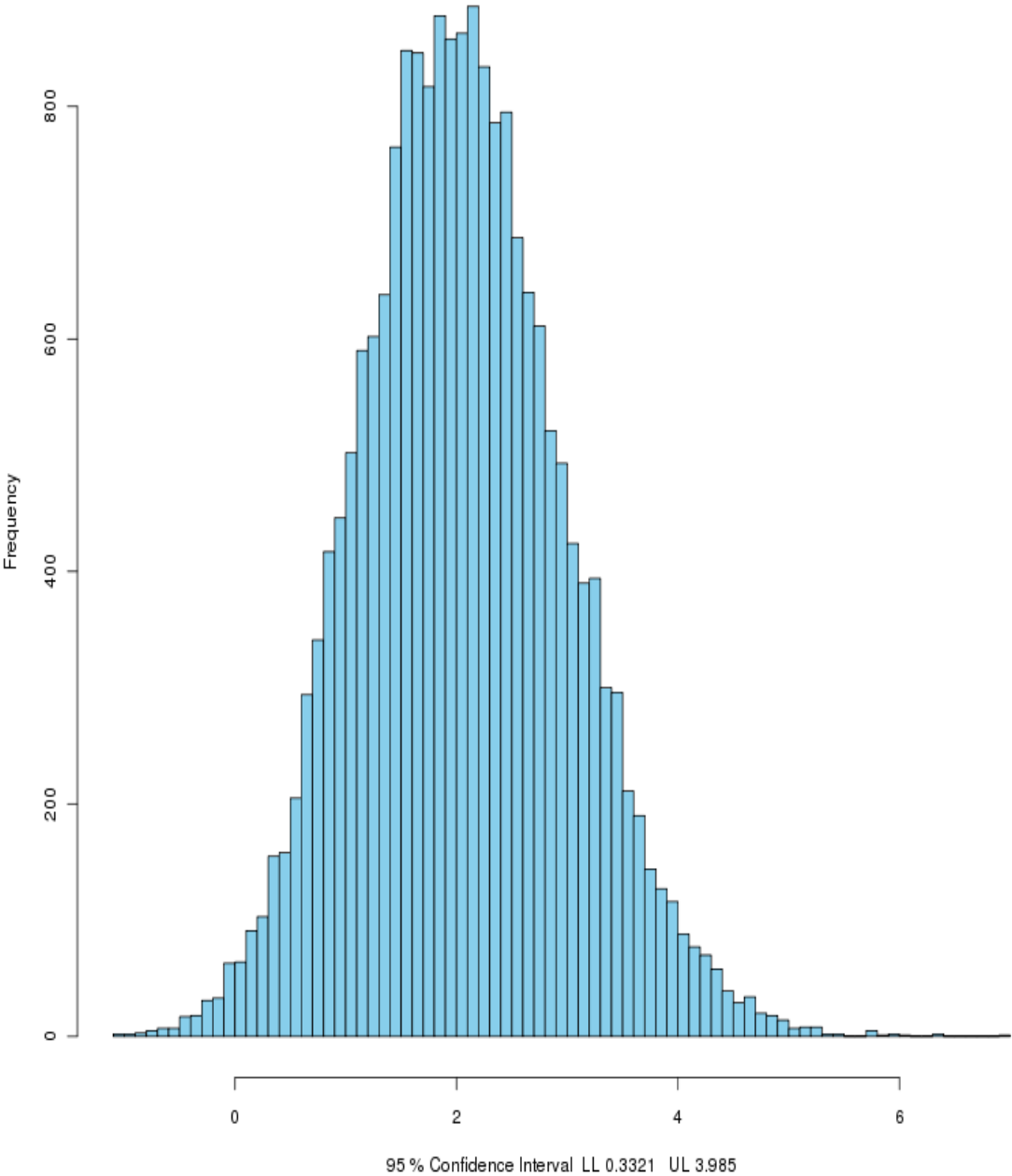
Degrees of freedom for the LESS constrained model= 8

OUTPUTS:

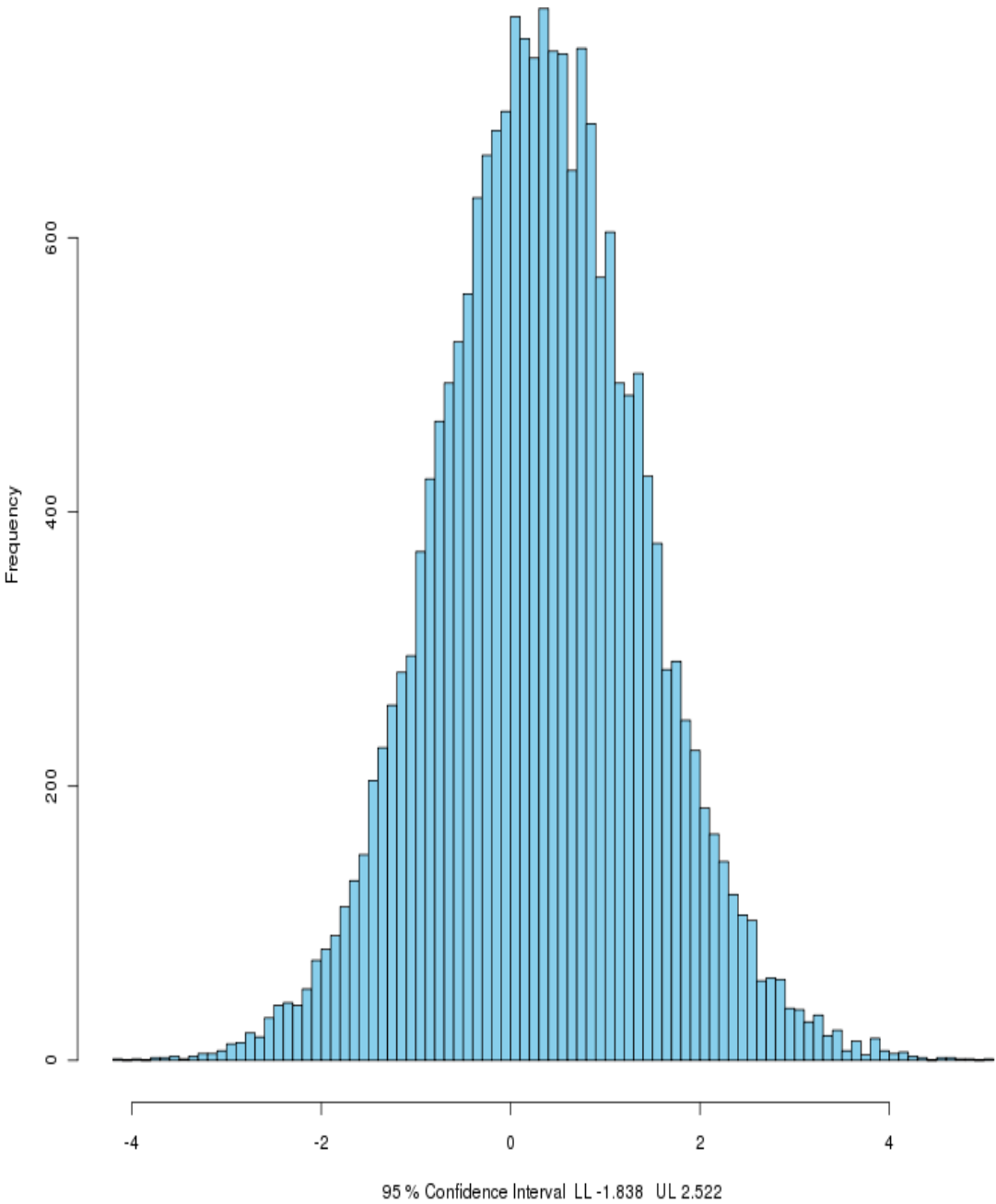
Satorra-Bentler Scaled Difference = 43.3730 df = 1

Chi Square probability = 0.000000

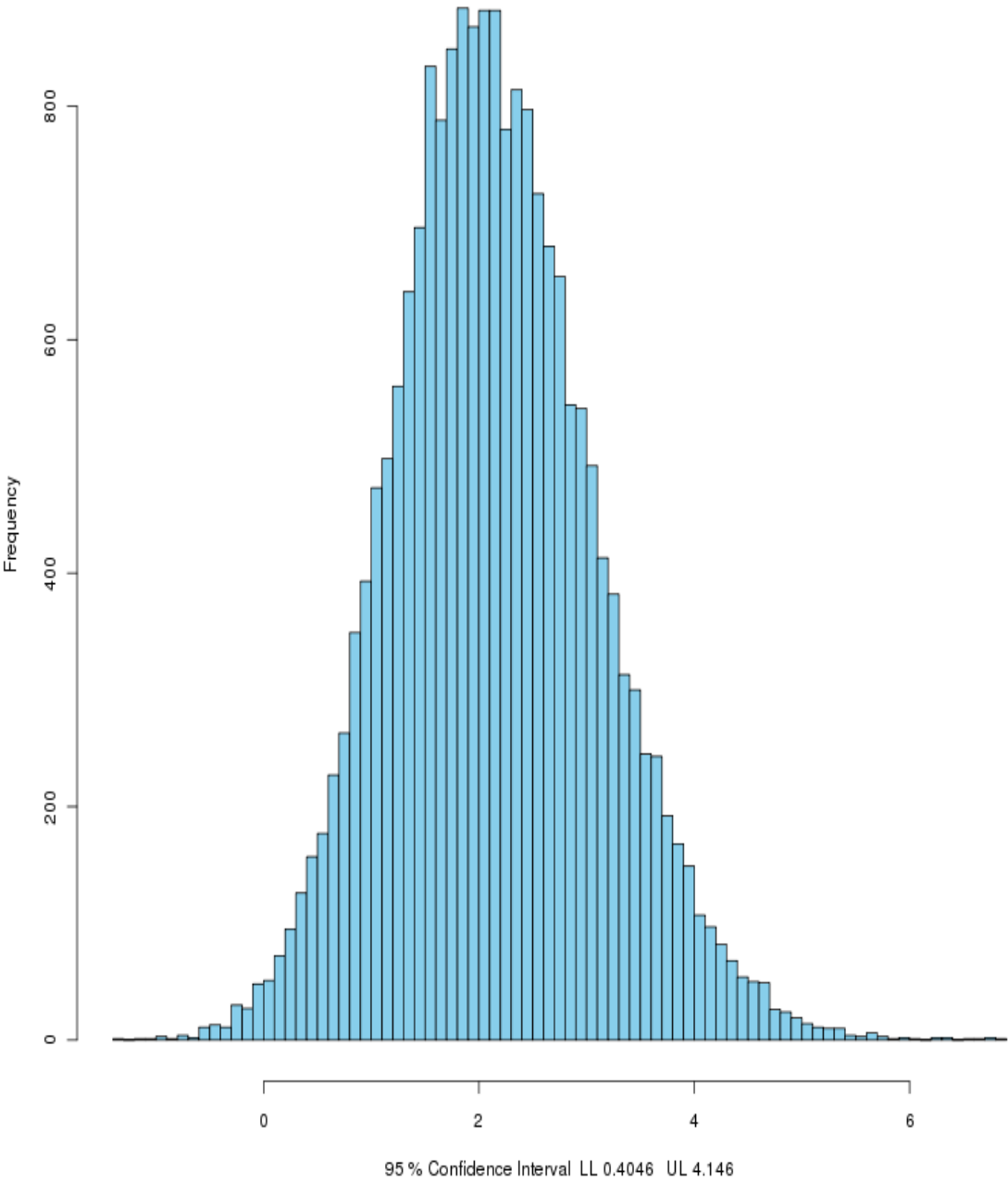
**Appendix G: Distribution of indirect effects for internal integration and RECOVER**



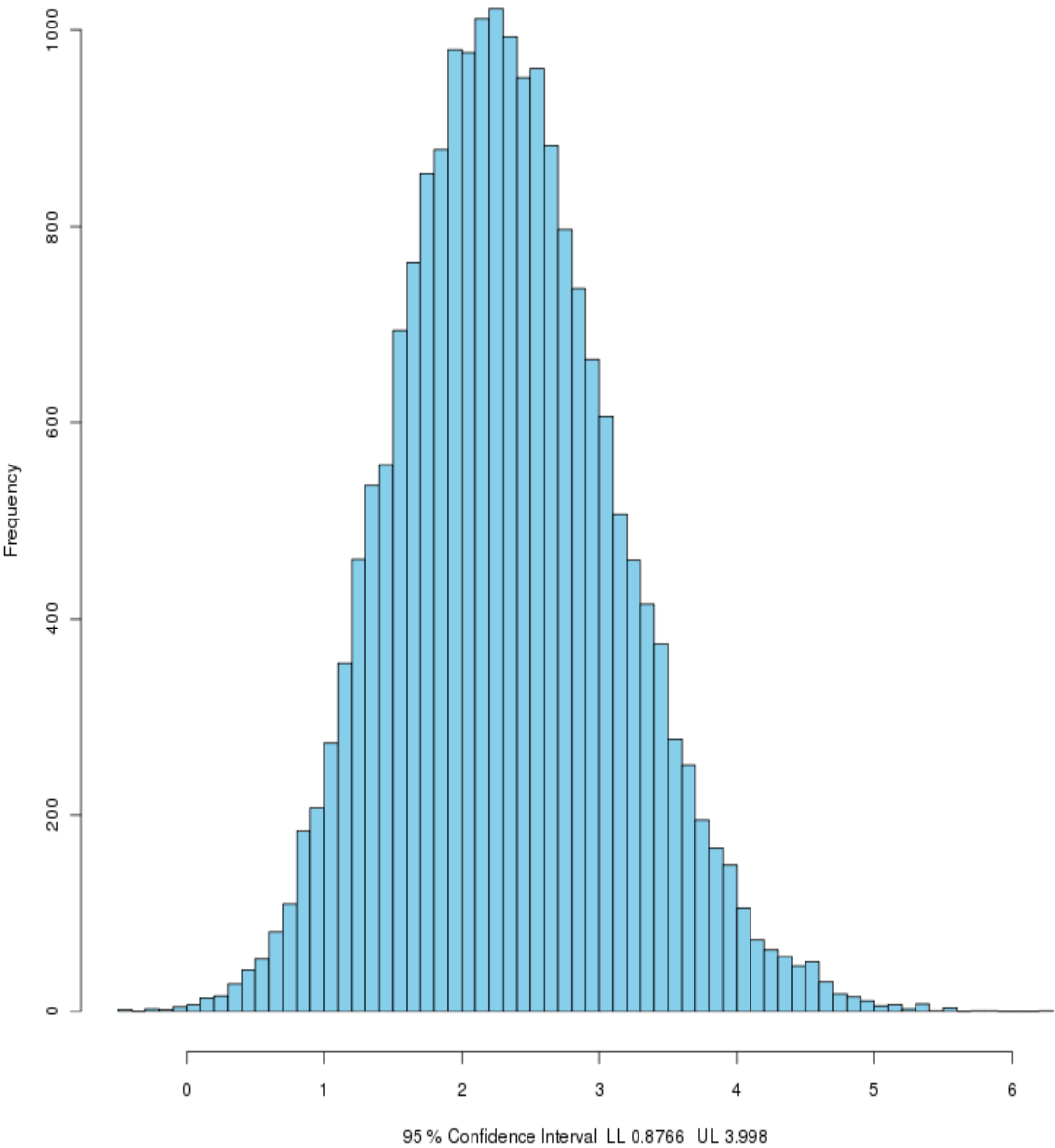
**Appendix H: Distribution of indirect effects for INFOSHR and RECOVER**



**Appendix I: Distribution of indirect effects for TRAIN and RECOVER**



**Appendix J: Distribution of indirect effects for WARN and PERF**





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